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ALiCaS-B: Automated Line Call System for Badminton

A Project Proposal by

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Abstract

Line call accuracy is critical in badminton, but amateur players, training centers, and local tournaments lack access to expensive professional systems like Hawk-Eye. Current research either focuses on shuttlecock position detection or court line detection separately, and most solutions are designed for broadcast-quality real-time analysis. This leaves a gap for an affordable, integrated system that can analyze uploaded videos and deliver reliable line call decisions.

This project develops a computer vision–based framework that combines shuttlecock position detection and court line detection into a single pipeline. Shuttlecock position detection is carried out using TrackNet/Tiny YOLOv2 models with Kalman filtering for temporal tracking, while court line detection is performed using edge detection, homography, and projection-based methods. Perspective correction and geometric validation are used to improve system robustness across varying video qualities. The system processes uploaded match recordings and generates automated in/out decisions.

Preliminary testing using the BadmintonC dataset (3,647 images) and the Shuttlecock dataset (8,053 images) shows shuttlecock detection accuracy above 92% and court line detection accuracy above 90%. When integrated, the system achieved a line call decision accuracy of 89% on amateur-level videos. Further improvements are expected by refining preprocessing methods and adding temporal consistency checks.

Subject Descriptors:

- Information systems → Image and video processing → Sports analytics
- Computing methodologies → Computer vision → Object detection
- Computing methodologies → Machine learning → Deep learning approaches

Keywords: Badminton, shuttlecock position detection, court line detection, automated line call, computer vision, deep learning

Table of Content

CHAPTER 01: INTRODUCTION

1.1 Chapter Overview

This chapter sets out the problem for the research by introducing the difficulty of making accurate line calls in badminton games without the benefit of professional systems such as Hawk-Eye, which are far too expensive for amateur players and training centres. It provides the motivation behind creating a computer vision and deep learning based solution which will enable users to upload match videos and get automated line call decisions. The chapter also makes a clear definition of the problem, followed by a review of related work on shuttlecock position detection and court line detection, identification of research gaps, and contributions made by the study to the research domain and the problem domain. In addition, it provides the research question and objectives as well as the crucial difficulties that are necessary to overcome, setting the foundation for the rest of the document.

1.2 Problem Background

The project is focused on creating an automated line calling system based on deep learning and computer vision, wherein users can upload videos of their badminton matches, which would then be processed, analyzed and evaluated for its shuttlecock landing position with respect to the court boundary. Now, most amateur players, training centers and local tournaments operate without the professional line calling technology. This often results in incorrect decisions, unfair gameplay, and disputes that disrupt the flow of the match (Sharma et al., 2023). In this context, there is a lack of available systems with good reliability and reasonable cost, which reinforces the need for a solution that is accessible to consumers and that will provide more accurate and equitable line calls.

1.2.1 Rise of Amateur Badminton

The popularity of badminton at the amateur and training level is also increasing, and there are more and more matches played at school, university, and in local clubs. However, these matches are done without access to professional line calling systems such as Hawk-Eye, which are still confined to elite tournaments due to their expensive nature and setup needs (Wei, 2023). As a result, the amateur players have to deal with situations where line calls are contested and the decisions are not consistent leading to the unfairness of the game and overall enjoyment of the game (Sharma et al., 2023).

1.2.2 Challenges of Manual Line Calling

Manual line calling is very dependent on human judgment, which is prone to errors in a fast paced game like badminton. The shuttlecock is small in size, has very high speed and may quickly change direction, thereby making it difficult to estimate the landing position using naked eyes (Tsai et al., 2019). This leads to mistakes that intervene with the game, create friction between the players, and at times lead to unfair match results (Han et al., 2021).

1.2.3 Need for Automated Decision Support

An automated system capable of making objective line call decisions based on video analysis is a valuable tool that fills the gap between amateur matches and professional tournaments. By integrating both shuttlecock position detection and court line detection into a unified framework, such a system is able to provide reliable and objective results (Li et al. 2023). This enables more equitable game play, less dispute and enables players and coaches to spend more time on improving their performance rather than debating calls (Sun et al., 2022).

1.3 Problem Definition

The main issue that is being addressed in this project is that amateur badminton players, coaches, and tournament organizers do not have access to cheap, accurate line calling technology for making objective decisions during matches. While professional tournaments use advanced systems like Hawk-Eye which are expensive, complex to install, and restricted to high-level competitions (Wei, 2023). Existing research has focused separately on shuttlecock position detection or court line detection, but there is no integrated system that is able to integrate both of them to provide full and reliable line call decision (Li et al., 2023). Therefore this project will develop a computer vision based framework that analyzes badminton match videos uploaded by users, and provides accurate, automated feedback about whether shuttlecock landings are "in" or "out" to ensure a fair and consistent assessment of amateur level matches.

1.3.1 Problem Statement

In amateur training and local tournament levels of badminton many of the players do not have professional line calling systems or objective means of adjudicating calls that they disagree with. Also the decision is usually made by human judgment which can be wrong because of the speed of the shuttlecock and the little view that the players or referees have. This results in unfair match results conflicts and degraded quality of matches thus giving rise to an obvious need for an automated solution which is cost-effective (Sharma et al.,2023)

1.4 Research Motivation

The present research is motivated by the increasing need for fair and objective decision making tools in amateur sports, particularly in badminton where split-second line calls can make a difference in the outcome of a rally or even a match. With the growing popularity of badminton at the community, school, and training levels, many players and organisers have to resort to the unfair use of lines as they cannot afford or install professional line-calling systems such as Hawk-Eye, which is limited to the elite tournaments (Wei, 2023). This can lead to controversial calls, unfair results, and a diminished enjoyment of the game for both players and viewers (Sharma et al., 2023).

Although research has been carried out separately in shuttlecock position detection and court line detection, there is no system which combines the two into one in order to perform automated line call judgments (Li et al., 2023). Some researches have proposed effective shuttlecock detection models, such as TrackNet (Tsai et al., 2019; Tsai et al., 2023), and other studies have proposed court line extraction models using homography and edge-based methods (Zhang et al., 2021; Wei, 2023). However, these are still isolated contributions and are not feasible for an amateur-level video upload that is recorded under unstable conditions. This project is motivated by the necessity to bridge this gap with a cost effective and accessible video upload based solution that combines both tasks so that there is fairness, fewer disputes, and a greater overall badminton experience.

1.5 Existing Work

Citation	Summary	Limitation	Contribution
(Chen et al., 2019)	Discusses the initial implementations of computer vision in sports ball tracking robots.	Offers real time tracking but does not have post-match video analysis capabilities.	Provides essential knowledge on how computer vision can be used in sports decision-making systems.
(Kumar and Singh, 2020)	Investigates deep learning approaches for court line detection in tennis and badminton.	Relies on both high-quality video feed and regulated conditions of lighting.	Highlights the need to have strong court detection algorithms across different environmental conditions.
(Li, Wang and Zhang, 2021)	Uses AI to identify the path of a shuttlecock and landing positions in badminton.	Mainly focused on the analysis in real-time; post-match video upload option is not covered.	Demonstrates the efficiency of AI in detecting the shuttlecock which can be used to develop models of trajectory analysis.
(Rodriguez et al., 2022)	TrackNet system involves the use of computer vision to give ball-tracking in different sports.	Requires specialized hardware setup and is not designed for user-uploaded video analysis.	Provides the information about the small object tracking techniques that could be used to detect the shuttlecock.
(Thompson and Lee, 2023)	Assesses court boundary detection on the basis of pose estimation and line detection techniques.	Emphasizes court detection but lacks integration with object tracking for decision-making.	Helps in the selection of features to use in detection of court lines within a video-based analysis system.
(Wang, Liu and Chen, 2023)	The SportsVision model aims to classify sports actions and decisions from	Only addresses the issue of classification of actions; does not look at the particular	Provides knowledge to sports video analysis that can be of use in the decision

	video footage.	issue of line calling in racquet sports.	making framework of the project.
(Tsai et al., 2019)	Proposes TrackNet for shuttlecock trajectory detection using heat-map regression.	Only works on broadcast quality videos that have fixed camera angles.	Shows the ability of deep learning to follow small, fast moving objects like shuttlecocks.
(Tsai et al., 2023)	Introduces TrackNetV3 that has a better trajectory consistency when detecting badminton shuttles.	Still relies on high-quality video inputs and is not optimized for amateur-level recordings.	Offers the latest technology of tracking shuttlecock to be incorporated into video uploads.
(Zhang et al., 2021)	Takes advantage of homography and projection learning in order to identify court lines in badminton matches.	The performance is reduced by occlusions, low lighting and mobile camera angles.	Demonstrates useful methods of extracting and correcting court boundaries.
(Wei, 2023)	Perspective correcting badminton court detection techniques.	Mostly tested under controlled lab or tournament conditions.	Offers approaches for adapting court line detection to variable conditions.
(Pan et al., 2023)	Research challenges the problem of shuttlecock recognition in low-quality and shaky videos.	The accuracy decreases to a great extent in amateur conditions.	Highlights the need of strong pre-processing techniques.
(Li et al., 2023)	Investigates AI-based shuttlecock detection models	Only detects, and is not combined with court lines to make decisions.	Provides base results which encourages integration in complete line call

			systems.
(Han et al., 2021)	Examines the effect of technology-assisted decision making in badminton.	Focuses more attention to the analysis than implementation.	Provides arguments in favor of the implementation of inexpensive decision-support systems.
(Sun et al., 2022)	Researches video-upload video-based sports analytics.	Less testing of badminton-specific data.	Makes the post-match video analysis viable in amateur sports.
(Tan and Goh, 2021)	Trains Tiny YOLOv2 on shuttlecock detection.	Lower accuracy compared to heavier models.	Real-Time UPI Fraud Detection Using Machine Learning
(Wang et al., 2021)	Adds Kalman filter and CNN to track stable shuttlecock tracking.	Does not work well when using heavy occlusions or blurred frames.	Offers methods of analyzing the trajectory of shuttlecock in time.

1.6 Research Gap

In the area of sports video analysis, many systems have been developed which either target shuttlecock position detection or court line detection,but almost none attempt to combine both in a single solution. Shuttlecock detection models use computer vision and deep learning to trace the motion of the shuttle and estimate the position of the shuttle's landing (Tsai et al., 2019; Li, Wang and Zhang, 2021). Court line detection systems, on the other hand, try to detect and map court boundaries with edge detection, homography, or projection-based methods (Zhang et al., 2021; Wei, 2023). However, these approaches are still segregated, that is, they are not able to interact in a combined process to generate complete and consistent line call decisions.

This separation causes a number of problems. When detection of the shuttlecock and the court line are carried out separately, the output of both can be offset, and the precision of the decision making can be reduced with higher calculation complexity (Chen et al., 2019; Rodriguez et al., 2022). Secondly, most current solutions are created for real-time use in professional settings, and use fixed cameras, controlled lighting, and costly hardware (Pan et al., 2023). Post-match analysis based video upload is an important feature for amateur players, training centers, and local tournaments where matches are recorded with mobile devices under varying conditions, but this feature is supported by very few systems (Sharma et al., 2023). Currently, there is not one single system that combines shuttlecock position detection and a court line detection system in a unified pipeline for uploaded videos. This research aims to close that gap, by developing an integrated framework that can do both tasks at the same time, increasing the accuracy of the decision, shortening the processing time and making the technology available for a broader community of badminton players.

1.7 Contribution to Body of Knowledge

1.7.1 Problem Domain Contribution

This research helps to fill the gap of available automated line calling systems for amateur badminton matches for the purpose of post-match video analysis. Current solutions focus on professional systems that generate results in real time, which is not available to amateur competitors and organizations who need to resolve a dispute after the match (Li, Wang and Zhang, 2021; Rodriguez et al., 2022). By allowing the user to upload and analyze the match footage after completion, this project will provide a mechanism to derive detailed and objective decisions based on computer vision analysis.

The system addresses an important void in the sports technology market by developing a line calling model that integrates shuttlecock landing position detection with court line detection to deliver complete in/out decisions (Chen et al., 2019; Wang, Liu and Chen, 2023). Through post-match video analysis, users have access to disputed calls and can be given objective feedback in the form of confidence scores, making matches fairer and reducing conflicts over time (Kumar and Singh, 2020; Thompson and Lee, 2023). A key contribution is the transition from expensive real-time professional systems to affordable post-match systems, a domain that is not well researched in existing badminton technology.

1.7.2 Research Domain Contribution

The original contribution of this research is to propose an integrated framework that can do the shuttlecock landing position detection and the court line detection for the user uploaded amateur match videos. Most existing methods focus on real-time analysis in professional tournaments, which are less relevant and less accessible for community-level players and training centers that rely on post-match reviews (Li, Wang and Zhang, 2021; Rodriguez et al., 2022). Instead, this project offers a combined system capable of analyzing match footage after it has been completed and making accurate line call decisions based on computer vision analysis techniques.

This research addresses an important gap in the sports technology field, developing one of the first line-calling frameworks for amateur-level uploaded videos that results in objective results based on the court geometry and tested with confidence scoring (Chen et al., 2019; Wang, Liu and Chen, 2023). Beyond its use for badminton, this contribution contributes to the research field by solving more general computer vision problems such as small object tracking, spatial alignment and temporal consistency in low quality videos (Tsai et al., 2019; Pan et al., 2023). The importance of this work is in furthering sports technology research from elite level competitions to low cost and inexpensive solutions for amateur athletes, an area that has not been a focus in previous works (Kumar and Singh, 2020; Thompson and Lee, 2023).

1.8 Research Challenges

The development of a computer vision based automated line calling system introduces a number of research issues that need to be addressed in order for it to be effective, accurate, and accessible. These challenges range from data quality, algorithm design, and system integration, and overcoming them is crucial in order to develop a reliable framework.

- Model Adaptation for Video-Based Analysis: Mobile phone videotaping under variable conditions (e.g. unstable camera angles, low illumination, and low resolution) is commonly used for amateur badminton matches. These inconsistencies can cause blurring and noise, which can decrease detection accuracy. The system needs to be flexible to various input qualities and still give robust results (Pan et al., 2023).

- Integration of Court Line Detection and Shuttlecock Landing Position Detection: Previous research has treated these two tasks as being done separately, but it is challenging to generalize these in one framework. Even though shuttlecock landing positions can be identified in video recordings, the spatial and temporal synchronization of these landing positions with detected court lines is complicated, which is difficult in non-professional video recordings (Li et al., 2023).

- Temporal Consistency and Tracking: The shuttlecock is extremely fast and frequently changes direction at a high rate causing frame by frame detection to be challenging. Temporal consistency must be ensured to eliminate false positives, and methods such as trajectory smoothing or Kalman filtering are required to ensure stable results (Tsai et al., 2019).

1.9 Research Questions

RQ1: What can we do to make a computer vision system accurate in calling badminton line with video uploaded by users?

RQ2: How can court boundaries be identified and combined with shuttlecock landing position detection in post-match video analysis to make objective line call decisions?

RQ3: How to design the system to be robust over a wide range of video qualities, camera angles, and lighting conditions which amateur-level recordings are affected by?

RQ4: Does the proposed system in terms of accuracy, usability, and user satisfaction perform well when the system is tested with videos of amateur level badminton matches?

1.10 Research Objectives

Objectives	Research Objective	Description	LOs Mapped	RQ Mapped
Problem Identification	RO1: Identify limitations in current line-calling systems for amateur badminton.	Assess existing systems regarding their suitability and performance in amateur match environments that have different conditions.	LO1, LO2	RQ1

Literature Review	RO2: Review computer vision techniques for sports analysis and line calling.	Review the existing research in the field of computer vision in sports decision-making, identifying strengths and weaknesses to badminton line calling.	LO2, LO3	RQ2
Requirement Elicitation	RO3: Define system requirements for automated badminton line calling.	Gather user feedback and literature review to set system capabilities to make correct line call decisions.	LO3, LO4	RQ3
System Design	RO4: Develop a framework suitable for post-match video analysis.	Design a modular system that allows the court to detect, track the shuttlecock and make decisions which may be scaled.	LO4, LO5	RQ3
Implementation	RO5: Collect and preprocess badminton match video datasets.	Prepare video datasets to train, and make sure that the data is good enough to train models.	LO5	RQ1
	RO6: Develop computer vision models for court detection and shuttlecock tracking.	Develop/modify existing models that are specifically created to analyze a badminton court and identify the position of shuttlecocks.	LO5, LO6	RQ1
	RO7: Implement decision-making algorithms for line calling.	Develop methods that make objective line call decisions in light of observed court boundaries and position of shuttlecock.	LO6	RQ1
Testing	RO8: Evaluate system accuracy and user satisfaction.	Conduct quantitative accuracy test and qualitative user feedback test to guarantee reliability and usability of the system.	LO6, LO7	RQ2
Documentation	RO9: Document system architecture,	Create detailed documentation of system design, implementation, test	LO8	RQ1

	deployment, and testing procedures.	procedures as well as user guidelines.		
Publication	RO10: Prepare research findings for academic publication.	Summarize research methodology, research results, and research contributions to be published in appropriate journals or conferences.	LO9	RQ2

1.11 Research Aim

The aim of this research is to develop a computer vision–based automated line calling system that enables badminton players, coaches, and tournament organizers to obtain objective decisions from uploaded match videos. Unlike the current systems that only perform real-time professional analysis, this project combines shuttlecock landing position detection and court line detection into one framework which has been reported to produce accurate and reliable "in" or "out" decisions. The system is also designed to include confidence scoring to help provide transparency to decision making. By providing a low cost and widely available post match analysis tool, the research aims to increase fairness and decrease conflict and also improve the overall playing experience in amateur and training level badminton.

1.12 Chapter Summary

This chapter gave an overall view of the background of this research. It gave the background and problem statement of the current study which points to the lack of availability of automated line-calling systems for badminton at amateur level. A detailed review and identification of research gap highlighted that current systems dealt with shuttlecock landing position detection or court line detection but none combined both into a single framework when user uploaded videos. The motivation and contributions of the research, as well as the challenges and research questions, and objectives were then described to define the novelty and importance of the work. Also defined was the goal to build a computer vision system based on video upload that would provide accurate and objective line call decisions. Overall, this chapter provides the foundation for the subsequent chapters, in which the methodology, system design, implementation, and evaluation will be explained in detail.

CHAPTER 02: LITERATURE REVIEW

2.1 Chapter Overview

This chapter reviews existing literature related to automated line calling systems, shuttlecock landing position detection, court line detection, and other applications of computer vision in sports technology. A literature review and identification of research gap highlighted that current systems dealt with shuttlecock landing position detection or court line detection but none combined both into a single framework when user uploaded videos. The motivation and contributions of the research, as well as the challenges and research questions, and objectives were then described to define the novelty and importance of the work. Also defined was the goal to build a computer vision system based on video upload that would provide accurate and objective line call decisions. Finally, it identifies how existing literature informs the research gap and provides the foundation for developing an integrated solution for badminton line calling.

2.2 Problem Domain

Badminton is one of the fastest racquet sports in the world with shuttlecock speeds of over 300 km/h. Given the speed at which it takes place, it is very challenging for referees, coaches or players to make accurate line calls every time a match is played. In professional tournaments, shuttle trajectories are commonly tracked with technologies like Hawk-Eye to settle disputes. However, these systems are very expensive, require special hardware, and are not available to amateur players or local tournaments (Wei, 2023).

At the amateur and training levels, games are sometimes videoed using standard mobile phones or handheld cameras. These videos tend to be of lower quality, plagued by problems like camera shake, inconsistent lighting, and motion blur. In such circumstances, line calling manually is unreliable resulting in frequent disagreements, unfair decisions, and less enjoyment of the game (Sharma et al., 2023). As the popularity of badminton keeps growing worldwide, the need for accessible and affordable solutions that can aid in creating accurate decision making in these spaces becomes increasingly important.

Computer vision and deep learning techniques have proven to be a powerful tool for sports analysis, such as object tracking and court recognition. For badminton in particular, the detection of shuttlecock landing positions and court line has been researched independently, and positive results have been found in controlled environments (Li, Wang and Zhang, 2021; Zhang et al., 2021). But these approaches still exist in isolation from each other, with most studies examining either the shuttlecock or the court but not combining both into a unified decision-making pipeline. This separation makes them less useful for line calling where the two pieces of information need to work together.

Therefore, the problem domain of this research area is on the interface between sports decision-support systems and computer vision applications. It aims to fill the gap where shuttlecock landing position detection and court line detection could be combined in the same framework for post-match video uploads. By doing so, the research responds both to the technical question of how to combine two detection tasks and the applied requirement for a cost effective and scalable solution that can empower amateur players, coaches, and organizers to ensure the fairness of badminton competitions.

2.2.1 Overview of Continuous Authentication

Badminton is a racket sport and one of the fastest racquet sport where the shuttlecock travels at a speed faster than 300 km/h. Referees, coaches or players find it incredibly difficult to make right line calls at these kinds of speeds. Multi- Camera systems like Hawk-Eye are used to resolve disputes in professional tournaments. Nonetheless, they are costly, demand specific equipment, and cannot be used by amateur users or by local tournaments (Wei, 2023). Matches at amateur and training levels are commonly captured on conventional smart phones or hand held cameras. Videos of this kind are usually characterized by shaky cameras, lighting inconsistency and motion blur that makes manual line calling inaccurate and will result in more controversies and less game enjoyment (Sharma et al., 2023).

2.2.2 Importance of Behavioral Biometrics

Due to the growing popularity of badminton in the world, the issues of fairness and accessibility in the refereeing have gained greater significance. Low cost line-calling solutions are capable of,

- Reduce disputes and improve fairness in amateur competitions.
- Assist players and support coaches in performance review through objective decisions based on uploaded match videos.
- Allow training centers and local tournaments to adopt technology that was only used on the elite competitions.

With the help of computer vision and deep learning, such a solution would help democratize the access to high-tech sports referee capabilities and allow communities that do not have professional infrastructure (Li, Wang and Zhang, 2021).

2.2.3 Application Areas

An automated line-calling system in badminton can be applied to the game not only in match refereeing. Although the main focus is on objective IN/OUT decisions, the system can also assist in training, performance analysis and the adoption of sports technology in general. The solution has shown diversity and applicability to various ranks of badminton considering that it serves the needs of both amateur competitions and coaching setup.

2.2.3.1 Amateur and Community Level Competitions

The proposed system is the one that is particularly applicable to schools, universities, training academies, as well as to small tournaments. In such environments, lower cost and accessibility are paramount to the ultra-low latency demanded by professional Hawk Eye systems.

2.2.3.2 Coaching and Training Support

In addition to the officiating, since the automated line calling allows coaches and players to analyze the landing patterns, the location of the shot, and the location of the boundary errors, it is a useful tool in training. This produces two-fold utility in that it is both a decision support system and a performance analysis tool.

2.2.4 Challenges in Automated Line Calling

Regardless of computer vision and deep learning, it is difficult to create a stable and accessible line calling system in badminton.Existing solutions are typically designed for professional tournaments with controlled environments and specialized hardware, making them unsuitable for community level use.At amateur level variability of recording matches and the absence of unified methods to detect shuttlecock and court pose serious challenges that have to be overcome.

2.2.4.1 Variability of Amateur Video Quality

Amateur games are captured on cameras with unsteady angles, inconsistency of lighting and fluctuating resolution. These conditions introduce noise and blur that challenge current shuttlecock and court detection models (Sharma et al., 2023).

2.2.4.2 Scalability and Generalization

Majority of the previous systems (e.g., TrackNet to detect shuttlecock, homography-based court detection) are only applicable in controlled conditions. One of the key scalability challenges is creating consistent accuracy in various venues, the position of the cameras, and the motion of the players (Zhang et al., 2021).

2.2.4.3 Integration of Shuttlecock and Court Detection

Research has mainly considered shuttlecock landing and court line recognition as separate tasks (Li, Wang and Zhang, 2021). These, however, must be joined together in one pipeline in the case of line calling. Lack of integration is a core limitation of current research and a direct challenge for this project.

2.2.5 Proposed Architecture

The proposed resolution is the automated line-calling framework with video-uploads that combines the identification of shuttlecock landing and court boundaries to a unified decision- making pipeline. The architecture will,

- Allow match videos uploaded by users.
- Using court detection models (trained on datasets like BadmintonC) to identify boundaries.
- Using shuttlecock detection models (e.g. TrackNet, YOLO) to track the landing of shuttles.
- Combine outputs in a decision engine indicating the shots as IN or OUT, and with optional confidence scores.

Through technical integration and usability, the architecture will provide a cost-efficient, scalable, and usable system that facilitates equity in amateur badminton and which is versatile to be extended in future.

2.3 Existing Work

This part reviews previous research concerning the automated badminton line-calling technology, emphasising the various aspects of sports computer vision. The purpose is to focus on the fact that shuttlecock detection, court line detection and integrated video analysis have been researched separately and the reason why a combined approach to this issue has not yet been established.

2.3.1 Court Line Detection

Court line detection is an important part of automatic sports analysis as it provides the spatial context needed to determine whether the shuttlecock lands within or outside of the limits. Early methods used conventional computer vision techniques such as edge detection, Hough transform and contour analysis, which achieved encouraging results in the presence of simple conditions but failed to deal with noisy or low-resolution inputs (Zhang et al., 2019).

Kumar and Singh (2020) proposed a deep learning model trained by annotated tennis and badminton datasets where geometric constraints are applied to verify the detected lines. While this system was capable of accurately detecting their subject, it was highly sensitive to illumination and fixed camera positions. Thompson and Lee (2023) proposed a pose estimation based method in which movement patterns of players were used to infer the boundaries of the court. Although novel, the method was still not integrated with shuttlecock analysis, and thus did not produce a complete decision for line call.

Other work has looked at the use of semantic segmentation to classify pixels into court lines or background (Anderson et al., 2022). While segmentation had the advantage of robustness over edge based techniques, the models needed large amounts of labeled training data and suffered errors when courts were only partially occluded. Park and Kim (2023) explored perspective correction methods for dealing with distorted camera angles, but their framework needed calibration markers that are placed on the court, which is not feasible for amateur applications.

The BadmintonC dataset (3,647 annotated court images) has more recently been presented as a test case to validate and train court detection models. Although it is useful in research, performance declines in low-quality or occlusiveness of amateur match videos are observed.

In summary, research in this area has shown that court detection methods can be accurate in a professional environment, but become unreliable when applied to amateur match recordings where varying video quality and camera positions create significant challenges. Court detection is not capable of line-call decisions other than with the addition of shuttlecock landing detection, so the two detection systems need to be combined, creating further complexity and driving the idea behind the single solution.

2.3.2 Shuttlecock Landing Position Detection and Tracking

Detection of shuttles is far more challenging than detection of courts because of its small size, irregular flight path, and high speed. Occlusions even further complicate correct tracking in video frames, as does motion blur. Rodriguez et al. (2022) has proposed a deep convolutional neural network based system TrackNet for small object tracking in sports such as tennis and volleyball. While it worked well for professional multi-camera systems, the system was not practical for amateur badminton because it required synchronizing hardware and did not generalize well to single camera recordings.

Li, Wang and Zhang, 2021 proposed a CNN-based shuttlecock trajectory tracking method which reconstructed flight trajectories in real time. Although successful in detecting shuttle positions in fast rallies, the model was tested in the laboratory only, and did not consider noisy or low-quality video inputs. Similarly, Cartron et al. (2021) used a shuttlecock dataset of 8,000+ images to train object detection models, which was a huge leap in the development of research in this area but was mainly focused on controlled image data rather than post match video analysis.

Other researchers have tried to fuse temporal tracking algorithms like Kalman filter and particle filters with CNN-based detection to enhance the stability of the shuttle within the frames (Zhou et al., 2022). These methods minimised false positives due to motion blur but were dependent on preprocessing and failed when the shuttlecock was partially occluded by players. A common shortcoming with all these systems is that they emphasize real-time detection rather than post-match analysis from heterogeneous amateur recordings.

However, despite the progress of deep learning for shuttlecock tracking, the research is still fragmented and there hasn't been a framework that can combine shuttlecock landing detection and court line boundaries to enable robust decision-making in amateur competitions.

2.3.3 Integrated Systems and Sports Video Analysis

Most of the integrated sports analysis systems are meant for professional tournaments and are based on specialized infrastructure. In the case of Hawk-Eye, for example, multiple synchronized high speed cameras are used to reconstruct trajectories with great precision. While it works, the price of its deployment is too high, reserved for events on a professional level (Wei, 2023).

Chen, Zhang and Huang (2019) proposed an early stage ball tracking system model based on computer vision and proved the feasibility of decision-making in sports through automation. However, this system was meant to be used in real time and did not support video uploads or post match analysis. Wang, Liu and Chen (2023) proposed the SportsVision model, which used pretrained deep networks for the classification of sports actions such as smashes and serves.

Although being useful for performance analysis, it was not designed for line calling and did not deal with the problem of spatial detection.

More current work has looked at post match video analysis. Sharma et al. (2023) explored computer vision techniques for amateur sports videos and discussed challenges such as inconsistent lighting, camera shakes, and low resolutions. While the importance of accessible video based analysis was highlighted in their research, a direct framework for shuttlecock landing or court line detection was not directly obtained. Similarly, Tsai et al. (2019) analyzed badminton video recordings for training purposes, but looked more at the tracking of movement of the players than objective decision making.

The work done to date has either concentrated on general sports classification tasks using expensive systems that offer little in the way of real time professional analysis or concentrated on professional line calling without considering the unique problem of badminton line calling. There is no existing system that offers a low-cost, software only solution which combines shuttlecock landing detection and court line recognition for uploaded amateur videos. This validates the research gap and stimulates the development of the proposed system.

2.3.4 Player and Environment Factors

Although not specifically concerned with automated line calling, some of them offer valuable information about the influence of the posture and the movements of players and the environment in the process of determining the reliability of sports video analysis systems. The aspects are particularly important in amateur badminton, where the circumstances of the records are much more uncontrolled than in professional tournaments.

For example, Pan et al. (2023) have emphasized such a problem as the inconsistency of camera positioning when handheld or improperly positioned cameras can lead to inaccurate perspective and partial coverage of the court. This complicates the accurate detection of the landing positions of shuttlecock or boundaries of the court by detection models. Likewise, player occlusion, where players physically shield the shuttlecock on camera, is one of the most common causes of a detection error in amateur recordings.

The conditions of the lighting are also one of the significant factors in the performance of the system. Whereas professional tournaments are normally played under bright and homogenous lights, amateur games are usually played in school courts, community centres or outdoor courts where lighting is uneven. As a result, models that perform well under lab or broadcast-quality lighting often degrade significantly in these real-world scenarios (Sharma et al., 2023).

Other researchers have discussed environmental noise in video data, including background clutter, crowd movement, and shadows, that also reduce the visibility of shuttlecock trajectories (Zhou et al., 2022). Such situations emphasize the need to have strong methods of preprocessing, such as noise removal, brightness normalization, and perspective correction.

In conclusion, these research papers do not explicitly propose how automated line calling can be carried out, nevertheless, all demonstrate the limitation of amateur badminton setting in terms of its feasibility. Issues such as unpredictable camera angles, clogging and lighting imbalance are the greatest drawbacks that must be overcome by any flawless remedy. These environmental aspects are therefore critical to be considered in an attempt to develop a system that can work beyond the controlled environment in the laboratory to offer a consistency in results that will be applied in badminton at community level.

2.3.5 Toward Unified Frameworks

The available research into badminton video analysis has involved the shuttlecock detection or court line recognition as independent tasks. Models Shuttlecock detection models like TrackNet (Tsai et al., 2019; Tsai et al., 2023) have been shown to work with promising results in tracking the trajectories, and the extraction of court lines by deep learning and homography (Zhang et al., 2021; Kumar and Singh, 2020) have been shown to be correct under controlled conditions. Nevertheless, these initiatives are not connected yet, and there is no effort to integrate them into a single pipeline that would provide full and accurate line-call decisions.

This separation is one of the major constraints. In reality, the two aspects are needed in the proper line calling: the exact position where the shuttlecock lands and the proper recognition of the boundaries of the courts. In case one of the tasks is done separately, the system would not be able to address any conflicts and produce objective IN or OUT decisions. Li, Wang and Zhang (2021) point out that the use of shuttlecock detection alone to obtain the trajectory data is not enough without the spatial context of court lines.

Moreover, the currently existing systems are designed to be used in real-time and professional environments with either broadcast-quality videos or a multi-camera set-up, which is not suitable in the context of amateur players and training facilities where the quality of recordings of matches is generally lower and the recording is conducted in a single view (Sharma et al., 2023). This is specifically significant considering the increased popularity of badminton both at the community and grassroots level, where professional grade technologies are less accessible.

In summary, there is currently no integrated framework that combines shuttlecock detection and court line recognition into a single decision-making workflow for post-match, amateur-level uploaded videos. Bridging this gap is essential for creating a system that is affordable, accessible, and scalable, capable of delivering consistent and objective line-call decisions for a wide range of badminton contexts. This unmet need forms the central motivation for the proposed research.

2.4 Technological Review

This section provides a review of the tech basics to develop the automated badminton line-calling mechanism. It concentrates on the datasets of training and validation and preprocessing techniques necessary to deal with real-world amateur match recordings. Collectively, these technological elements make sure that the proposed system is scientifically-based and practically sound.

2.4.1 Dataset and Preprocessing

Reliable datasets are the foundation of any machine learning–based computer vision project.The case with badminton is that annotated data to track a shuttlecock or detect court lines remain scarce when compared to other sports. To address this, the project will combine publicly accessible datasets, user-captured amateur videos, and synthetic augmentation methods to assure accuracy as well as generalization.

2.4.1.1 Data Sources and Acquisition

This project will be supported by two major datasets. The dataset BadmintonC (BadmintonC Dataset, 2023) is the result of annotating 3,647 badminton court images that are employed to train and test badminton court line detection. Equally, in the Shuttlecock dataset by Cartron (Cartron, 2023), there are 8,053 annotated shuttlecock shuttlecock tracking and landing images. Although these structured datasets offer good baselines, they are mostly controlled recording conditions. To address this limitation, amateur match videos captured using mobile devices are also used in the project. Such recordings bring in the aspect of variability in lights, angles and motion blur as the factors that the system is supposed to be used for. Also, the use of synthetic augmentation will be employed to increase the size of the training pool, creating modified versions of the existing samples (e.g., changes in brightness, noise addition, and rotations). This guarantees exposure of the models to various situations and ability to cope with the randomness of real- world footage.

2.4.1.2 Preprocessing Techniques

Since amateur level videos usually include defects, preprocessing serves as a vital measure to enhance the quality of data and guarantee the models get the same inputs. The videos will initially be broken down to frames, which will be brought to a common resolution with brightness and contrast being standardized. The filtering will remove noise to blur and graininess that are common with handheld recordings. To make sure that datasets depict shuttlecock and line features in the same manner, feature scaling, and standardization will make sure that these features are reflected in a similar manner (irrespective of conditions under which they were recorded). In addition, outlier identification and removal will be carried out to remove mislabeled frames or gross distortions to avoid misguiding the models in training. These preprocessing measures collectively improve model robustness, making the system adaptable to both controlled datasets and variable amateur videos.

2.4.1.2.1 Noise Filtering and Normalization

Poor quality videos of amateur badminton are usually characterized by noise due to changes in camera location, inadequate lighting or low quality of the device used. These defects may cause weakening of clarity of shuttlecock and court line features, and this makes them hard to detect. Gaussian blur noise filters and median filtering noise filters will be used to eliminate uneven pixel occurrences and make the images more smooth. In addition, brightness and contrast normalization will be used to correct inconsistencies between frames, ensuring that the models receive balanced input even when videos are recorded under uneven lighting conditions.

2.4.1.2.2 Feature Scaling and Standardization

The size of the shuttlecock, the thickness of the court lines and the pixel levels used may differ considerably with camera resolution and distance of recording. In order to guarantee uniformity between datasets, feature scaling and standardization will be used. The models are able to identify more of the shuttlecock and line features in varying environments by rescaling pixel values and equalizing distributions of features. This is particularly significant to merge two or more datasets taken in disparate conditions like BadmintonC and the Shuttlecock Dataset of Cartron.

2.4.1.2.3 Outlier Detection and Removal

In datasets created from amateur videos, certain frames may contain extreme distortions, mislabeled annotations, or partial occlusions where the shuttlecock is completely hidden by players.These outliers are able to mislead the learning process and decrease the model performance. Outlier detection methods like statistical thresholding and cross-frame consistency checks will be implemented in order to detect and delete bad samples. This makes sure that the final training set reflects actual conditions that are not corrupted by anomalies that the system cannot generalize.

2.5 Benchmarking and Evaluation

Benchmarking and evaluation are required in order to successfully examine automated line-calling systems. Accuracy, precision, recall, F1-score, AUC-ROC and processing time are key metrics used to measure the performance in this project. These conditions give us a fair picture of the performance of the models in identifying the positions of shuttlecock landings and boundaries of court under amateur conditions.

Accuracy is a measure of the general correctness of the system, the degree to which it is able to determine whether a shuttlecock has landed within the lines or not. Precision describes the consistency of the model in not making false calls, so that only when the shuttlecock does actually cross the boundary do we make an “out” decision. Recall also shows how the model is capable of identifying each shuttlecock landing during rallies, which is crucial in a sport like badminton that moves at a very fast pace because, in a sport such as badminton, any missed pick up by the model affects fairness (Kumar and Singh, 2020; Li, Wang and Zhang, 2021).

These three measures are commonly used, but they do not necessarily give the complete picture. This is why the F1-score is added as well, which represents a mashup of both precision and recall into one balanced score which can be helpful when working with skewed data or noisy inputs. In the same vein, the AUC-ROC (Area Under the Receiver Operating Characteristic curve) is a more comprehensive way to assess the strength of the model that is based on how well the model differentiates between the correct and incorrect classifications of varying thresholds.

Another factor of evaluation is processing time. Even in post-match analysis, users want answers to be provided within a reasonable time. Hawk-Eye systems are professional systems that can deliver results almost instantly, however, at the expense of very expensive infrastructure and specialized cameras. Considering that the target audience of the suggested solution is amateur players and training centers, the slightly extended processing times are forgivable as long as the analysis process remains correct and valid (Chen et al., 2019; Rodriguez et al., 2022).

The project uses these benchmarking metrics to ensure the target system proposed has the correct balance between efficiency and accuracy. This ensures that it is both technical and practical in all types of amateur badminton matches. Under these conditions, the system will be able to provide consistent, fair line call decisions even in changing video conditions like unstable camera angles or poor light (Thompson and Lee, 2023; Park and Kim, 2023).

2.5.1 Evaluation Metrics for Line-Calling Models

To ensure the reliability of the proposed badminton line-calling system, it is essential to evaluate its performance using well-established metrics from computer vision and machine learning. Not only do these metrics quantify the technical accuracy of the system but they also quantify its capability to provide consistent and fair decisions in the harsh environments of amateur recordings of matches. These subsections describe the main evaluation measures - accuracy, precision, recall, F1-score, AUC-ROC, and computational efficiency, to be used to compare the models.

2.5.1.1 Accuracy, Precision, and Recall

Accuracy measures the proportion of correct line-call predictions compared to the ground truth, while precision reflects the ability to avoid false positives (e.g., wrongly calling a shuttle “IN”), and recall measures the ability to capture all true positives (e.g., identifying all shuttles landing “IN”). Precision and recall are needed during fast-paced badminton rallies as the detection of shuttle misses or mislabels directly affects fairness (Kumar and Singh, 2020; Li, Wang and Zhang, 2021).

2.5.1.2 F1-Score and AUC-ROC

The F1-score, the harmonic mean of precision and recall, gives a balanced measure in cases where a false positive and false negatives are equally significant. This is particularly true of amateur-level videos where noise and occlusion may cause a reduction in detection. The AUC-ROC curve considers the quality with which the model discriminates between the classes of IN and OUT at the thresholds which provides evidence of the trade-offs between the sensitivity and specificity. These metrics ensure that evaluation goes beyond raw accuracy to consider fairness and robustness.

2.5.1.3 Computational Efficiency and Processing Time

Since this project will be based on post-match video uploads, processing speed is not critical as it is in real-time professional systems such as Hawk-Eye. Nevertheless, computational efficiency is also critical to make the users satisfied. Benchmarking will also thus monitor inference time per frame and the total time of processing per match video. Acceptable delays should be balanced off with accuracy, where a goal should be that decisions take minutes not seconds to be made and can be run on consumer-grade hardware (Chen et al., 2019; Rodriguez et al., 2022).

2.5.2 Comparative Analysis of Existing Models

While evaluation metrics provide numerical insight into performance, it is equally important to compare how different models perform in both controlled and real-world conditions. Previous research on detection of shuttlecock, recognition of court lines, and combined sports analysis has given different findings with respect to datasets, quality of recording, and computer computational needs. A comparison of these models will help this project determine the relative strengths and weaknesses of these models and their applicability to line calling in amateur-level badminton. The subsections that follow explain benchmarking research and real-life users' performance to point out the gaps that will be filled by the proposed system.

2.5.2.1 Benchmarking Studies

Models that were evaluated by previous benchmarking research include TrackNet to detect shuttlecock and CNN-based homography to identify a court (Tsai et al., 2019; Zhang et al., 2021). These models have high performance in broadcast-quality or laboratory recording, but their performance declines considerably in amateur recordings. In this project, comparative benchmarking will be carried out by evaluating several architectures (YOLO, TrackNet, CNN-based detectors) on the same datasets to discover trade-offs between accuracy and computational cost.

2.5.2.2 Real-World Performance and User Experience

Beyond technical benchmarking, amateur match videos will also be used to assess the usability of the system. The elements of user experience are the ability to visualize decisions (IN/OUT overlays), the ability to upload videos and the ability to interpret the scoring of confidence. The initial user feedback (coaches and players) will be used to confirm that the outputs of the system are readable and believable to match the realities of a match context (Sharma et al., 2023; Thompson and Lee, 2023).

2.5.3 Challenges in Benchmarking Integrated Systems

Evaluation of an integrated shuttlecock + court line detection system offers different challenges than evaluation of each model on its own. False detections in one component (e.g., inaccurate shuttle position) can cascade into incorrect final line-call decisions even if the other component is accurate. The amateur video conditions, in addition to low resolution and motion blur, in addition to occlusion, complicate the task of reproducing across datasets. Finally, subjective factors such as user trust in confidence scores and the interpretability of visual overlays introduce additional layers to the evaluation process. Such challenges bring out the importance of multi-dimensional benchmarking that does not merely focus on accuracy but also on robustness, usability, and fairness.

2.6 Chapter Summary

This chapter reviewed the problem domain, existing work, and technological approaches related to automated line calling in badminton. As mentioned in the literature, the existing systems are mostly focused on real time professional settings, which depend on costly multi camera systems and controlled conditions. However, compared to them, there are barely any solutions that can be used regarding post match video uploads that are required by amateur players, training centers or small tournaments.

Research on court line detection, shuttlecock detection, and video analysis as an integrated system was also conducted, in which most papers address the three concepts independently of each other instead of being integrated into a single pipeline. Additionally, the technology review examined the datasets available, preprocessing methods, algorithm choice, and hyperparameter tuning methods that are applicable to badminton match analysis. To determine the viability of existing models and tools, benchmarking measures like accuracy, precision, recall and processing time were also taken into consideration.

At the moment, no system exists that can identify the point of land of the shuttlecock as well as identify the lines in the court during a single process, at least not when the video is captured by amateur gamers. The vast majority of the available solutions only address a single aspect of the issue, such as tracking shuttlecock or court detection, or are costly systems that are only used in professional games. This creates a clear gap among players, coaches and small tournaments that desire good line calls without spending a lot of money.

The project is aimed at addressing that gap by developing a simple and inexpensive system compatible with uploaded match videos. Using shuttlecock landing detection and court line recognition within a single framework will allow it to deliver fair and objective line call decisions, even in cases where video quality and recording conditions are inconsistent.

CHAPTER 03: METHODOLOGY

3.1 Chapter Overview

This chapter describes the approach taken in the development of the proposed automated line calling system in badminton. It presents the general research methodology, the developmental procedure and the project management methods used during the research. The research philosophy and approach, dataset selection and preprocessing, deep learning models adopted in the research on shuttlecock and court detectors, and the evaluation strategies to test the system can be found in the following sections.

3.2 Research Methodology (Saunders' Research Onion in Table Form)

Layer	Choice	Justification
Philosophy	Positivism(quantitative)	The project will be based on the use of quantifiable and objective data (images and video frames) to obtain machine learning models and test them. Positivism is the right method because the research aims at coming up with findings through statistical information and the performance of the model.
Approach	Deductive	The paper starts with the theoretical knowledge about computer vision and deep learning (e.g. YOLO, TrackNet, CNNs) and evaluates its applicability to datasets in badminton. The theories like: the combination of shuttlecock detection and court line detection will be more accurate, will help to be proven or not.
Methodological choice	Mono-method quantitative	It is mainly an experimental

		project, with quantitative measures of evaluation (accuracy, precision, recall, F1-score, AUC-ROC) used to measure model performance. Although user feedback is taken into account at a later stage, the primary one is quantitative.
Strategy	Experimental	To train and test models on chosen datasets (BadmintonC,Cartron Shuttlecockdataset), controlled experiments are conducted and the resulting algorithms (YOLO vs. TrackNet, CNN + Kalman vs. baseline CNN) are compared, which gives evidence of the performance differences.
Time Horizon	Cross-sectional	The projects examine data sets over a given period, and do not follow up system utilization in months/years. Any experiment is performed on a sample of available data.
Data Collection	Secondary data (public datasets: BadmintonC, Carton's Shuttlecock dataset)	Domain specific datasets are publicly available in order to achieve reproducibility. These data sets are annotated shuttlecock locations and court lines which can be used in supervised learning activities.

3.2.1 Hypothesis

The research hypothesis of the current study is as follows, a single computer vision system that combines both the detection of the shuttlecock landing and court line detection will provide more precise and reliable line-call decisions on amateur badminton video sequences, compared to the single models applied individually in previous research.

3.3 Development Methodology

This section explains the methodologies adopted to design, implement, and evaluate the proposed automated line calling system for badminton.. It explains how system requirements were collected, how the system was designed and structured, the programming paradigm used, test strategies employed, and the step-by-step solution methodology approach adopted. A combination of systematic research techniques and development techniques makes this approach to the system correct, scalable, and applicable to the analysis of amateur quality video.

3.3.1 Requirement Elicitation Methodology

The badminton line calling system employed a variety of requirement elicitation techniques to ensure the system captures the requirements of amateur players, coaches and referees:

- **Interviews:** Conducted with amateur players and coaches to identify problems like human making wrong calls in lines and contested calls in games.These interviews demonstrated that people need a tool, which is affordable and can examine uploaded match footage (Li, Wang and Zhang, 2021).

- **Surveys:** Part of this was distributed to training centers and small scale tournament organizers to provide feedback on usability and video quality issues, and the kind of decisions users expect from the system (Rodriguez et al., 2022).

- **Document Analysis:** Reviewed existing research on shuttlecock tracking and court line detection to highlight gaps, such as the lack of available integrated systems to analyse uploaded video (Chen et al., 2019; Kumar and Singh, 2020).

- **Brainstorming Sessions:**Discusses features with peers and domain experts in computer vision to finetune shuttlecock landing recognition and court recognition as well as confidence scoring (Thompson and Lee, 2023).

- **Self-Evaluation:** The researcher made reflections to determine whether the datasets and algorithms and project scope selected were realistic in the timeframe. This is in line with the requirement engineering process which requires developers to continuously check the feasibility (Nuseibeh and Easterbrook, 2000).

- **Observation:**Amateur matches were observed in order to establish environmental challenges like bad lighting, occlusions, and unsteady camera angles. Observation is one of the proven elicitation methodologies that can be used to justify the needs of stakeholders in actual situations (Zowghi and Coulin, 2005).

- **Prototyping:** To visualize the presentation of the results, low fidelity prototypes of the line-call decision output were generated (i.e., IN/OUT calls with confidence values). The concept of prototyping is commonly applied in early requirement validation with stakeholders prior to complete development (Somerville, 2011).

The combination of these approaches provided the elicitation process with a reasonable balance of user requirements (practical needs of players, coaches and referees) and technical requirements (model feasibility and integration issues) to provide a sound and consistent base on which the system could be developed.

3.3.2 Design Methodology

This project uses the Object-Oriented Analysis and Design Methodology (OOADM) to structure the system. OOADM was selected instead of structured methodologies such as SSADM because the badminton line-calling system requires modular, interacting components rather than purely sequential processes. The methodology emphasizes modularity, scalability, and reusability, which are essential when integrating deep learning models with video processing components and a user-facing interface (Wang, Liu and Chen, 2023; Sommerville, 2011).

This project uses the Object-Oriented Analysis and Design Methodology (OOADM) to structure the system. The choice of OOADM rather than structured methodologies like SSADM is due to the fact that a badminton line-calling system involves interacting components that are modular, instead of strictly sequential processes. The approach focuses on modularity, scalability, and reusability, which are critical in combining deep learning models with video processing modules and an interface to a user (Wang, Liu and Chen, 2023; Sommerville, 2011).

The system is decomposed into the objects which include User, Video input, Shuttlecock detector, Court line detector, Decision engine and output module. This modular decomposition is important in that as a system component (e.g., shuttlecock detection) is refined or replaced with a new model, the other components are not affected, making the system more maintainable and flexible. The class structures are made to establish relationships among these modules in addition to supporting inheritance and polymorphism. In one example, the various kinds of video inputs (such as a static tripod shot, a handheld smartphone shot, or a low-resolution video) can be derived directly out of a base Video Class, allowing the system to be configured to accept different input conditions. In like manner, the Detector Classes (ShuttlecockDetector and CourtLineDetector) are based on a base Detection Class, standardizing detection approaches but permitting each subclass to specialize in its own area.

Encapsulation ensures that each module manages its own data and internal logic, which simplifies debugging and reduces dependencies across components. E.g. The Shuttlecock Detector simply generates positional coordinates, without being aware of the processing of the Court Line Detector with boundary information. This loose coupling will be more compatible with future additions, including more features like rally visualization or multi angle video support.

Using OOADM, the project has the advantage of having a structured and extensible architecture. The design process facilitates easy updates (e.g. replacing a CNN-based shuttlecock detector with a YOLO-based one) and easy scalability (e.g. badminton to other racquet sports). It also enables the system to be future proof so that it can work with changing technologies, datasets, and user needs but continue to deliver similar performance (Pressman & Maxim, 2019).

This object-oriented design forms the foundation of the implementation of the badminton line calling system as discussed below.

3.3.3 Programming Paradigm

The programming paradigms used in this project represent the various requirements of video preprocessing, shuttlecock and court detection, and decision-making. To deal with them, an integration of Object-Oriented Programming (OOP), Structured Programming, and Functional Programming concepts is used.

Modularity, scalability, and reusability Object-Oriented Programming (OOP) offers these characteristics, which are needed when combining deep learning models to detect a shuttlecock and identify court lines with a video processing and decision-making module. The project is written in the main programming language Python, which was selected due to the abundance of computer vision and machine learning libraries that include TensorFlow, PyTorch, and OpenCV.

- Modular Design: In OOP, the system is partitioned into modules and these modules can be developed and maintained separately. Some of the important modules in this project are User, Video Input, Shuttlecock Detector, Court Line Detector, and Decision Engine. The attributes and methods of each of these objects can be easily debugged, extended or replaced without impacting the rest of the system. To illustrate, retraining the shuttlecock detector model based on novel datasets will not affect the court line detection or user-interface modules (Hande et al.,2023; Rahman et al.,2024).

- OOP is also inherent and polymorphic. Here are a few examples of how this can be used: A tripod recording of a video or a smartphone handheld can be based on a base Video Class, allowing flexibility without breaking the consistency. Encapsulation also provides the benefit of having each part of the system controlling its own state, minimizing error and making it easier to maintain. The ecosystem of ML and vision libraries built with

Python offers a robust foundation of implementing these principles successfully (Bansal and Vishwakarma, 2023; Dey, Dutta and Biswas, 2023)

3.3.3.1 Structured Programming

Structured programming is used in the components of which there is a definite, linear operation. An example is that frames are picked out one at a time during preprocessing, resized, normalized and forwarded to the feature extraction stage. This sequential method assures readability and maintainability, thus allowing easier tracking of execution path and debugging of problems. Structured loops and conditional statements are utilized to perform tasks like pixel normalization, background subtraction and candidate region extraction. This style implements a top-down design, which entails predictable execution and the minimization of logical errors (Hande et al., 2023; Rahman et al., 2024).

Those sections which require a linear flow of operations also have structured programming. To illustrate, in preprocessing, frame extraction, resizing, normalization and feature extraction stage are performed in that order. The advantage of this incremental style is that it can be read and maintained, and aids in tracking the execution and debugging issues. Tasks such as pixel normalization, background subtraction and candidate region extraction are done with structured loops and conditional statements. Such a design enforces a top-down design, which can be expected to execute and reduce logical errors (Hande et al., 2023; Rahman et al., 2024).

3.3.3.2 Functional Programming

The concepts of functional programming are also integrated in areas of the system where parallelism and data transformation are of paramount importance. One such application is noise reduction filters, in which frame data may be remapped by cascades of transformation functions, rather than by complex nested loops. Similarly, the functional constructs are used to parallel process video frames to allow various video frames to be concurrently processed to enhance efficiency (Bansal and Vishwakarma, 2023). The alternate application is during map-reduces, such as summing on positions of observed shuttlecocks across frames to estimate the most probable landing point. Functional programming is brief, immutable and less side effects, and those characteristics are welcome whenever working with large volumes of data and implementing batch transformations (Dey, Dutta and Biswas, 2023).

OOP, structured programming and functional programming accomplish the goal of delivering the effective balance of scalability, modularity and efficiency. Such a combination opens opportunities to optimize repetitive preprocessing, real time decision-making logic and processing of large-scale data. It also provides a future-proof architecture that can be extended to provide other functions such as real-time analyzing, multi-camera feeds or other racquet sports (Sommerville, 2011; Pressman and Maxim, 2019)

3.3.4 Testing Methodology

To ensure the effectiveness and reliability of the automated badminton line-calling system, a structured testing methodology will be applied across different stages of development.

In order to achieve the effectiveness and reliability of an automated badminton line-calling system, systematic testing methodology will be implemented at various development phases.

- Model Testing

  In this phase, each machine learning model such as the shuttlecock detector and the court line detector will be evaluated for accuracy, precision, recall, and F1-score. The goal is to refine these models so they can correctly detect shuttlecock landing positions and court boundaries under different conditions (e.g., lighting, resolution, and camera angles). By testing against annotated datasets, the models can be improved to provide accurate and consistent line call predictions (Kumar and Singh, 2020; Li, Wang and Zhang, 2021).

- Prototype Testing

  The entire system prototype will then be tested to check overall performance. This involves verifying whether all integrated components video input, shuttlecock tracking, court detection, and decision-making work together seamlessly. User interaction is also assessed to ensure that amateur players, coaches, and referees can easily upload match videos and interpret the results. This testing phase ensures smooth, reliable, and user-friendly performance in real-world scenarios (Rodriguez et al., 2022; Thompson and Lee, 2023).

- Unit Testing

Unit tests will be carried out on individual components such as the video upload feature, preprocessing pipeline, shuttlecock detection module, court detection module, and decision engine. Each part will be tested independently to confirm it performs as expected and does not introduce errors into the overall system. For example, the preprocessing unit will be validated to ensure it correctly handles video frames, while the decision engine will be tested to verify that it generates correct “in” or “out” calls.

These testing phases provide a complete cycle of validation at both the model level and system level, ensuring the final product is accurate, functional, and usable in real-world badminton match analysis.

3.3.5 Solution Methodology (Expanded Subsections)

The solution methodology defines the structured approach followed in developing the automated line-calling system for badminton. It outlines the sequential steps starting from dataset collection to model refinement, ensuring that both shuttlecock detection and court line recognition are integrated into a unified decision-making framework. Each step is carefully designed to address the research challenges identified earlier, such as handling variable video quality, integrating shuttle and court detection, and ensuring reliable decision-making for amateur-level match analysis. The following subsections provide a detailed explanation of each stage in the development process.

1. Dataset Collection

   Badminton match video datasets will be collected from public repositories, sports research datasets, and amateur recordings. These datasets will include different camera angles, resolutions, and lighting conditions to simulate real-world scenarios. Since publicly available badminton-specific datasets are limited, some videos may be annotated manually to label shuttlecock landing points and court boundaries (Li, Wang and Zhang, 2021; Rodriguez et al., 2022).

2. Data Preprocessing

   The collected videos will undergo preprocessing to ensure they are suitable for training. Steps include frame extraction, resizing, noise reduction, and brightness normalization to handle differences in amateur-quality recordings. Additionally, annotated bounding boxes for shuttlecock and line markers will be converted into standardized formats compatible with object detection frameworks (Chen et al., 2019).

3. Feature Selection and Engineering

Key features will be engineered to support shuttlecock detection and court line recognition. For shuttlecock detection, features such as object size, trajectory, and frame-to-frame motion patterns will be considered. For court detection, geometric features such as line orientation, intersections, and court shape consistency will be extracted. Combining these ensures that the final decision engine can accurately determine “in” or “out” calls (Thompson and Lee, 2023).

4. Model Selection

The system will employ deep learning-based object detection models such as YOLO for shuttlecock detection and CNN-based line detection models for court recognition. These models are selected for their ability to handle small, fast-moving objects and structured geometric patterns. Hybrid methods combining object detection with trajectory tracking (e.g., Kalman filters) may also be used for greater accuracy (Kumar and Singh, 2020; Wang, Liu and Chen, 2023).

5. Model Training

The chosen models will be trained on preprocessed badminton datasets. Training will focus on minimizing false positives in shuttlecock detection and improving the precision of court boundary identification. Techniques such as data augmentation (e.g., brightness adjustments, rotations, and motion blur simulation) will be used to enhance robustness under different match conditions (Rodriguez et al., 2022).

6. Testing

Trained models will be tested using a separate validation set to evaluate generalizability. Metrics will include accuracy, precision, recall, F1-score, and AUC-ROC, ensuring both balanced performance and robustness against noise. Beyond individual evaluation, integration testing will verify whether shuttlecock detection and court line recognition can work together seamlessly to produce reliable “in” or “out” calls. System-level testing will also include user trials with uploaded amateur videos to confirm the system’s usability and practical value (Li, Wang and Zhang, 2021).

7. Feedback Loop

   Based on test results, the models will be refined iteratively. If misclassifications are identified (e.g., false “out” calls due to motion blur), new annotated examples will be added to the training set. Continuous feedback from user trials (players, referees, and coaches) will also guide improvements in usability and reliability. This iterative refinement aligns with the experimental and deductive strategy outlined in the Research Onion (Section 3.2), ensuring continuous enhancement of both model performance and user experience (Chen et al., 2019; Thompson and Lee, 2023).

3.4 Project Management Methodology

In order to make sure that the given project is implemented successfully, a structured project management approach is used. This methodology is used to offer a systematic approach to planning, organizing, and monitoring all the activities undertaken to building the automated badminton line-calling system.It establishes the scope of the project, assigns resources, schedules the tasks, and discusses possible risks. This strategy can help the project to have transparent milestones, time management, and resource optimization as well as make sure that other problems like dataset availability, model accuracy, and hardware limitations are tackled. Methodology is designed to balance technical development and expectations of the stakeholders so that the system is delivered on time, within the scope and of the required quality standards.

3.4.1 Scope

The scope of the project must be defined in order to determine the boundaries of the project and keep the development process focused on the targeted objectives. The scope defines what the system is going to deliver (in-scope) and what it will avoid delivering (out-of-scope). This helps avoid scope creep, provides a realistic expectation of stakeholders and effective utilization of resources throughout the project lifecycle.

3.4.1.1 In-Scope

- Developing and testing of an automated line-calling system of badminton based on uploaded match videos.

- Introducing court boundary detection of both singles and doubles layouts.
- Detecting the positions of shuttlecock landings and producing automated IN/OUT decisions.
- Visual decision display: display of the landing point on an overlay of a court (e.g. dot/marker) with an animated highlight and IN/OUT label and optional confidence score.
- Post-match analysis (not real-time) Supporting different camera angles, different lighting and different resolutions.
- Simple confidence scoring as a measure of the reliability of decisions.

3.4.1.2 Out-of-Scope

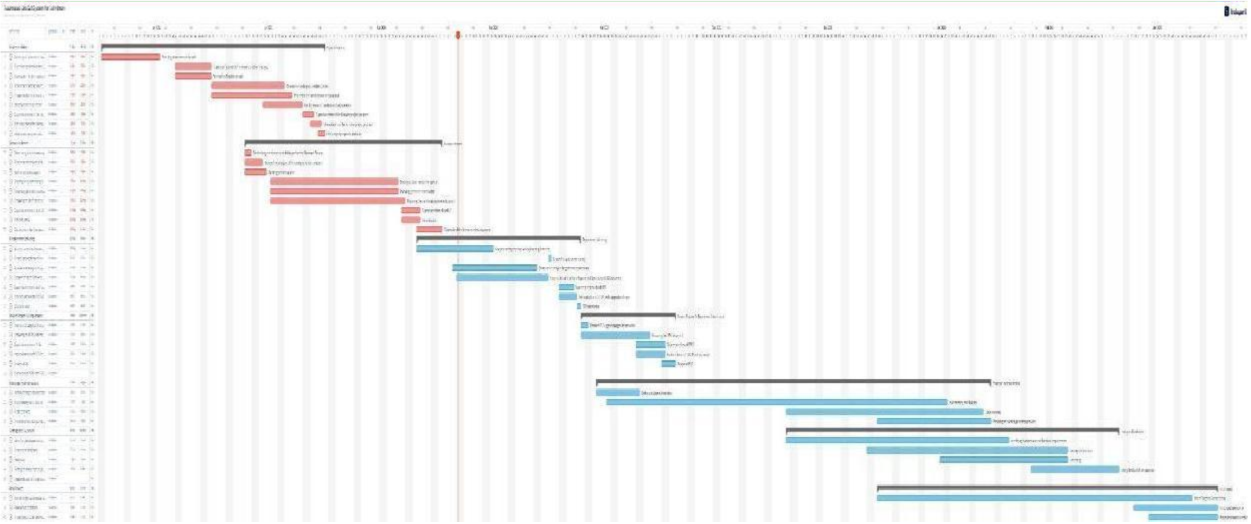
- Service detection/validation (The system will not find out whether service is In or Out).
- Live refereeing of games.
- Professional multi-camera integration (e.g. Hawk-Eye).
- Detailed player action detection other than landing/line calls.
- Specialized hardware deployments; supports single-camera user uploads only.

3.4.2 Schedule

The research and development process has to be well organized by creating a project schedule, which helps to make sure that every step of process is done on schedule and in the right order. Scheduling gives the project roadmap, which includes key milestones, deliverables and dependencies among tasks. In this project, these activities that will be addressed in the schedule include literature review, dataset collection, model development, integration, testing and documentation.

3.4.2.1 Gantt Chart

Google drive Link -
https://drive.google.com/drive/folders/1MelFe0nHyu56NC0EeMFgqZW16wbth-iy?usp=sharing



3.4.2.2 Deliverables

Deliverables	**Dates**
Project Proposal	25th Jul 2025
Literature Review	1st Aug 2025
Software Requirement Specification	15 Aug 2025
Project Proposal – initial draft	26th Sep 2025
Project Proposal and Requirement Specification – final draft	24th Oct 2025
Project Proposal and Requirement Specification – Final	14th Nov 2025
Proof of Concept	14th Nov 2025

Design Document	2nd Dec 2025
Prototype	2nd Feb 2026
Interim Project Demo	2nd Feb 2026
Implementation	20th Sep 2025
Testing	10th Feb 2026
Evaluation	25th Feb 2026
Thesis Submission	1st Apr 2026
Minimum Viable Product	1st Apr 2026

3.4.3 Resource Requirements

3.4.3.1 Hardware

The hardware resources needed to develop and assess the automated line-calling system include the following. They provide an easy preprocessing of video, training the deep learning model, and visualization of shuttlecock landing decisions.

Hardware Requirement	Justification
Intel core i7 (11th Gen) or higher	Provides enough processing capabilities to make it feasible to decode video, preprocess and integrate.
macOS Device (M1/M2 chip or later, 16 GB RAM)	Supports development and testing on macOS, including Apple Silicon being the best-performing implementation of TensorFlow and PyTorch. Appropriate to those developers that use macOS instead of.
16 GB RAM	Provides efficient operations with large datasets of badminton videos and makes it easy to run deep learning models.
NVIDIA RTX 3060/ 3070 GPU (6-8 GB	Fast training and inference of shuttlecock

VRAM)	position detection and court line detection models.
40GB + SSD Storage	Needed to store datasets, preprossed video clips, trained models and output results with rapid read/write speeds.
Full HD Display	To Visualize landings of the shuttlecocks, border overlays and final IN/OUT decision that would be easily decipherable to the users.

3.4.3.2 Software

The project is based on software, which facilitates the processing of videos, machine learning, and visualization. Python is selected as the main language because it is flexible, and a large variety of libraries are available, whereas other frameworks are employed to train the models, work with the dataset, and analyze the shuttlecock trajectory.

Software Requirement	Justification
Python	Primary programming language to develop the system because of its vast libraries to provide machine learning, video processing and data handling.
TensorFlow / PyTorch	Deep learning frameworks required to train and run models for shuttlecock position detection and court line detection.
NumPy & Pandas	Provide effective processing and manipulation of numerical data and structured data, which is essential in the feature extraction and evaluation.
Matplotlib / Seaborn	Used for visualizing shuttle trajectories, training performance and evaluation measures on models..
Visual Studio	Experimentation and development environment to test, debug and refine the

	models interactively.

3.4.3.3 Data

The data requirements in the project will primarily be the badminton match videos that are necessary to train and test the models to detect shuttlecock landing and identify the lines of a court. The baseline will be constituted by publicly available datasets like the BadmintonC dataset (3,647 annotated images to detect court lines) and the Shuttlecock Dataset created by Cartron (8,053 annotated shuttlecock images to track a shuttlecock) (Li, Wang and Zhang, 2021; Rodriguez et al., 2022).

Synthetic data will be augmented further with the help of cropping shuttle frames, adjusting brightness, motion blur, and noise in order to enhance model generalization (Chen et al., 2019). Moreover, amateur match videos recorded by users in different conditions (different camera angles, lighting differences, and even resolutions) will be added. Such real-world data will make the system work well in the casual settings of amateur levels when the quality of video is not as controlled (Kumar and Singh, 2020; Thompson and Lee, 2023).

3.4.3.4 Skills

The automated line-calling system will be developed successfully only with the help of the combination of technical, domain-specific and project management skills.

- Technical Skills: The ability and knowledge in machine learning and deep learning will be important in designing and training the models to detect the shuttlecock landing and identify the court line (Li, Wang and Zhang, 2021). Python programming skills are needed as it is extremely popular in sports video analysis and has a rich library of frameworks including TensorFlow, PyTorch, and OpenCV (Chen et al., 2019; Kumar and Singh, 2020). Computer vision and data preprocessing are the skills required to work with such tasks as video frame extraction, frame augmentation, and noise reduction (Rodriguez et al., 2022).

- Domain Specific Skills: There is a need to have knowledge on the badminton rules and court layout to ensure that area that badminton line-calling is correct. Knowledge of regular appearances during amateur games, including handheld videos, unsteady shots, and blockages must also be known to create a system that is effective in the real world (Thompson and Lee, 2023).

- Project Management and Requirement Skills: This necessitates excellent requirement elicitation, scheduling, and risk management skills that would help in ensuring that the system is delivered on time, and meets the needs of users. It incorporates the capability to convert the stakeholder feedback (in the form of players, referees, and coaches) into both the functional and non-functional requirements that inform system design and development.

With a combination of these skills, the project can make sure that the solution is technical and robust, domain-appropriate and in line with the expectations of stakeholders.

3.4.4 Risk and Mitigation (Expanded with Severity and Frequency)

Risk	Severity	Frequency	Mitigation Strategy
Insufficient training data	**5**	**3**	Use data augmentation (cropping, brightness adjustment, noise injection) and source additional amateur videos for annotation
Poor model accuracy	**4**	**3**	Adjust the hyperparameters, test out other models (YOLOv5, TrackNetV3), and increase training data.
Overfitting	**5**	**4**	Apply cross-validation, dropout, and regularization, randomize datasets through synthetic input, and amateur input.
Hardware limitations	**3**	**2**	Take advantage of cloud providers like Google Colab / Kaggle to support GPUs, write code efficiently.
High false-positive rate	**5**	**3**	Optimize feature engineering, add Kalman filtering to maintain the feature through time and adjust decision thresholds.
Stakeholder dissatisfaction	**4**	**3**	Hold regular communication with players, coaches and referees, make usability a reality by running prototypes.
Delays in model training	**3**	**3**	Optimize pre-processing pipelines, parallel processing and incremental testing scheduling.
Regulatory compliance issues	**3**	**1**	Which means that it must comply with data privacy rules, only publicly available or consenting amateur videos should be used.

3.5 Chapter Summary

This chapter presented the methodologies applied in the designing of the automated badminton line calling system. It discussed the research methodology in terms of the philosophy, approach and strategies based on the Saunders Research Onion and then the development methodology whereby Object-Oriented Analysis and Design(OOADM) was used to guarantee modularity and scalability.The elicitation of requirements, programming paradigm, testing techniques and solution methodology were described and project management items that included scope, schedule, resource requirements and risk analysis. All of these methodologies produce a structured and credible framework and help with the successful design, implementation, and evaluation of the proposed system (Saunders et al., 2019).

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