# Enhancing Sports Performance with Big Data and Machine Learning-Powered Predictive Analytics

**Submitted By:**

Rokib Hasan
ID: 221-35-923
Department of Software Engineering
DAFFODIL INTERNATIONAL UNIVERSITY

**Supervised By:**

MD. SHOHEL ARMAN
Assistant Professor
Department of Software Engineering

**DAFFODIL INTERNATIONAL UNIVERSITY**

**Department of Software Engineering**

**Faculty of Science and Information Technology**

**Supervisor Approval Form**

| | | |
|---|---|---|
| Fall 2025 | B.Sc. In SWE | Campus: DSC |

| Student Name | Student ID |
|---|---|
| Rokib Hasan | 221-35-923 |

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|---|---|
| | |
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Supervisor Signature

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Name of Supervisor
Date: 15-11-2025

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**(i)** The thesis contains a novel, integrated framework for football tactical analysis that utilizes a proprietary computer vision and explainable AI pipeline. Premature public disclosure could compromise the potential for patent filing and technology transfer.

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Date : 17 November 2025

Enhancing Sports Performance with Big Data and Machine Learning-Powered Predictive Analytics


STUDENT'S NAME

Rokib Hasan

ID: 221-35-923


Thesis submitted in fulfillment of the requirements

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# DEDICATION

This thesis is dedicated to my family, whose unwavering faith and endless sacrifices have been my foundation and strength. Your love and encouragement have illuminated my path and made this achievement possible.

And to every aspiring data scientist and sports enthusiast, may this work inspire you to explore the beautiful intersection of technology and human potential.

## ABSTRACT

In today's football, the use of "Big Data" continues to rise in importance but there remains a substantial distance between the wealth of tactical information contained within full-match footage and what actionable, interpretable insights coaches can extract. Existing analytic work typically employs the type of discrete event statistics that do not provide information on the dynamic spatial-temporal development of team tactics across the entire full match period. What's more, the complex AI models of choice for such applications generally function as black boxes,making trust and applicability challenging. The latest new BIG-XAI model framework for the football performance analysis has been proposed with big data and XAI to resolve these shortcomings.

The approach defines an end-to-end workflow starting from automatic analysis of full-match broadcast videos. The system is built upon a custom object detection model from fine-tuned YOLOv8 architecture. The DeepSORT (Deep Simple Online and Realtime Tracking) algorithm is used in conjunction to result stable storing of player trajectories. The pipeline also includes camera motion compensation through homography estimation to project player positions onto a top-down view of the pitch in order to estimate key spatial-temporal features, such as player speed, covered distance and team formations. More importantly, an XAI layer is embedded via saliency maps (Grad-CAM) and feature importance analysis (SHAP) allowing to transparently explainable descriptions of the models tactical insights in human language.

Experiments show that the proposed framework is highly effective. A strong mAP@0. 5) of 0.677, and achieves excellent performance on tactically important classes: Player (AP: 0.990), Referee (AP: 0.995), Goalkeeper (AP: 0.871), and Goalpost (AP: 0.928). This robust detection allowed accurate player tracking,team determination and successful extraction of physical performance measures. The XAI module successfully converted complex model outputs to meaningful visual and textual explanations, effectively recognizing relevant events like possession turnover and putting in a broader context performance metrics such as ball possession for the coaching staff.

In summary, this study represents an important step forward in providing full match tactical analysis through the development of a comprehensive interpretable AI framework which goes beyond historical events of play to deliver a dynamic, transparent and actionable profile of the evolution of tactics over the course of an entire competitive match. It connects machine learning sophistication and football coaching needs, establishing a new bar for trustable and acceptable AI in sports analytics.

**Keywords:** Sports Analytics, Explainable AI (XAI), Computer Vision, Object Detection, Tactical Analysis, Machine Learning, Football. YOLOv8.

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## LIST OF SYMBOLS

| Symbol | Description | Unit / Domain |
|---|---|---|
| P | Precision | [0, 1] |
| R | Recall | [0, 1] |
| F1 | F1-Score (harmonic mean of Precision and Recall) | [0, 1] |
| mAP@0.5 | Mean Average Precision at IoU threshold of 0.5 | [0, 1] |
| mAP@0.5:0.95 | Mean Average Precision over IoU thresholds from 0.5 to 0.95 | [0, 1] |
| IoU | Intersection over Union | [0, 1] |
| box_loss | Bounding box regression loss | |
| cls_loss | Classification loss | |
| dfl_loss | Distribution Focal Loss | |
| t | Time or frame index | s or frame # |
| $\boldsymbol{H}$ | Homography matrix for perspective normalization | 3x3 matrix |
| $\phi$ | SHAP value (feature contribution) | Real number |
| $Cx,Cy$ | Camera motion components in X and Y directions | pixels/frame |
| $IDk$ | Unique track identifier for object $k$ | Integer |

## LIST OF ABBREVIATIONS

| Abbreviation | Full Form |
|---|---|
| AI | Artificial Intelligence |
| AP | Average Precision |
| CNN | Convolutional Neural Network |
| DBSCAN | Density-Based Spatial Clustering of Applications with Noise |
| FPS | Frames Per Second |
| GNN | Graph Neural Network |
| Grad-CAM | Gradient-weighted Class Activation Mapping |
| KPI | Key Performance Indicator |
| ML | Machine Learning |
| mAP | mean Average Precision |
| PRISMA | Preferred Reporting Items for Systematic Reviews and Meta-Analyses |
| RQ | Research Question |
| SHAP | SHapley Additive exPlanations |
| SLR | Systematic Literature Review |
| XAI | Explainable Artificial Intelligence |
| YOLO | You Only Look Once |
| YOLOv8 | You Only Look Once Version 8 |

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# CHAPTER 1

# INTRODUCTION

## 1.1 Background of the Study

The footballing landscape of today is shaped more and more by data. The fight for competitive advantage have driven clubs and analysts beyond the commonly used metrics such as goals, passes, and possession (Wang, 2023). Time-motion and tactical principles of sports are common daily practice aims for sport scientists, since the motivational basis for applying spatial-temporal game-related data in specific periods or situations would allow such training to have a remarkable positive impact. They describe what happened from moment to moment—a pass was made, a shot was taken—but little information about how and why the events occurred is generated: key contextual factors such as player positioning, team shape, or coordinated tactical activity are ignored (Choustoulakis & Pastelakos, 2024).

In recent years, the rise of big data technologies, powerful ML algorithms and advanced computer vision has opened up a lot of potential. It is possible to automatically analyze full-play videos to generate diverse spatial-temporal information including players' positions, team formations, and tactic event transformations – Fujii (2025). These elements ensure a comprehensive insight into the game and develop an understanding of team strategies, as well as player roles. Yet a large roadblock still stands in the way—many of these AI-powered systems are not explainable. Although the complex deep learning models show to provide a high accuracy in pattern detection, however, they are considered "black boxes" which directly provide outputs without an explicit reasoning process (Silvino et al., 2025). This opaqueness also constrains the trust and practical usage of such tools by coaches and video analysts, who need understandable actionable insights to inform their decision-making (Plakias et al., 2025).

This study attempts to bridge these gaps by introducing an explainable AI engine using video analytics, machine learning predictive models, and tactical profiling. This is supposed to be a shift from looking into isolated match events toward interpretable, cross-match insights based on the flow of the entire game in order to support tactical and performance decisions for the coach.

## 1.2 Problem Statement

Existing football performance analysis methods rely mainly on discrete event statistics or data from wearable sensors that naturally do not possess the rich tactical and spatial intelligence contained in full-match videos. The current analytic tools cannot capture the dynamic aspects representable by excluding for example player formations and positioning in real-time during competitions.

Recent studies in big data analytics in sports (Wang, 2023), AI-based tactical analysis for sports (Choustoulakis & Pastelakos, 2024), predictive model to evaluate play efficacy during a match (Fujii, 2025) and athlete profiling based on individual performance (Plakias et al., 2025) exist but there is a lack of universal interpretable system which integrates them. No such behaviorial analysis framework exists that integrates holistic full-match video analysis with a thorough use of advanced yet interpretable AI to deliver actionable and transparent insights for football coaches. This work aims to fill this gap by creating a new explainable AI framework that exploits full-match video analysis in order gain further and more understandable insights into football tactics and performance.

## 1.3 Research Gaps

Using a systematic review of current literature, the following essential holes in research are identified and targeted for investigation by this thesis:

### 1.3.1 Limited use of full-match video:

The majority of academic research and commercial software tools concentrate on the analysis of separate in-game events (C2 goals, passes or set-pieces). The gaming system is too much to handle while they are bombarded with the nonstop 90+ minute actual match play that’s where the real meaningful adjustments and game flow dynamics happen.

### 1.3.2 Underdeveloped computer vision for football tactics:

Although method for detecting and tracking of players and the ball in the game has evolved, most approach are not suitable to encode high-level tactical concepts how teams rearrange formations,how they trigger pressing or supports ones defence from attack and vice versa in a dynamic environment  such as game.

### 1.3.3 Lack of explainability:

The majority of advanced AI and ML models used in sports analytics function as black boxes. Their decision-making processes are not transparent, making it difficult for coaches and analysts to understand, trust, and act upon the generated insights, thereby hindering practical adoption.

### 1.3.4 Missing integration of different data types:

Video feeds, player tracking data,  biosensor data such as heart rate and psychological tests are typically analyzed separately. There is a need for a holistic model that aggregates multimodal data streams into a  comprehensive and contextual performance profile.

### 1.3.5 Neglecting full-match tactical evolution:

The time of tactics is often  forgotten. In most studies, only short extracts or snapshots have been analysed with no means  of examining how the on field general principles and formation develop during the entire match.

### 1.3.6 Limited adaptability across skill levels:

Models and systems already in place are usually ad-hoc designed on elite level competitions data. They are not readily applicable, nor easily scalable, in the amateur  or youth football scenario where data quality and tactical complexity are dramatically different.

## 1.4 Research Objectives

To achieve the abovementioned problem and research gaps, this paper sets out to attain the following main objectives:

### 1.4.1 Objective 1: Full-Match Video Data Integration

Create a machine learning model for automatic extraction and analysis of spatial temporal features (e.g., positioning of the players, team formations, and tactical changes) from full match football video content, not limited to traditional event-based data.

Implication: This will enable uninterrupted game flow analysis as well capture tactical transitions occurring during the full 90+ minutes of match time which can fill a void in the scarce use of full-match videos currently observed.

Performance measure: We will evaluate the performance in terms of player detection, formation recognition and tactical phase segmentation over all full match duration.

### 1.4.2 Objective 2: Explainable AI for Tactical Analysis

To incorporate explainable AI methods (e.g., saliency map, attention map or SHAP value) in order to enhance model interpretability and offer coaches actionable and transparent insights on match dynamics and performance assessment.

Contribution: It directly tackles the black-box characteristic of lots of current AI models, providing an understandable decision to practitioners such as coaches and analysts in their daily working routine.

KPI: Success will be measured by the clarity of visual explanations (expert), how coherent the explanations are with tacit understanding, and how well-aligned to qualitative coaching feedback.

### 1.4.3 Objective 3: Tactical Evolution Profiling Over Full Match

To develop a framework to monitor and visualize the evolution of team tactics, formations etc. over the course of an entire match.

Contribution: This objective tackles directly the gap of longitudinal tactical evolution analysis for football, in particular it delivers a dynamic perspective on team play.

The objectives and quantitative assessment of the funded research: The impact of the proposed work shall be obtained by quantitatively evaluating the detected tactical changes versus expert-coded ground truth, with respect to - accuracy and precision in determining transition times.

## 1.5 Scope and Limitations of the Research

The scope of research is limited as follows to have clearer focus and also to make it manageable:

### 1.5.1 In-Scope:

Video-level (90+ minutes) analysis for full-match professional football matches.

Extraction of low-level features: player positions, team formations, and tactical plays.

Application of computer vision methods to object detection, multi-object tracking and formation recognition.

Application of Explainable AI (XAI) techniques such as saliency maps, Grad-CAM and SHAP for model interpretability.

Testing on annotated (publicly available) datasets (e.g., Metrica Sports, StatsBomb); validation performed with expert assessment of metrics such as accuracy and interpretability.

### 1.5.2 Out-of-Scope:

Incorporation of non-visual modalities, including psychological, physiological, or wearable sensors data.

Predictability of final game result/winning probability modeling.

Live injections and analysis during matches; after-match data are prefered.

Comprehensive time-series study for all three levels of competition (i.e., amateur, youth); emphasis on first side competitions.

## 1.6 Significance of the Study

The contribution of the proposed research is two-fold, one liberal- theoretical level and the other at a practical- football business level:

### 1.6.1 Theoretical Contribution:

It contributes to the domains of sports analytics, computer vision and explainable AI with a new integrated architecture that overcomes these limitations in prior art becoming suitable for providing full-match tactical analysis as well as explainability.

### 1.6.2 Practical Contribution:

This is the motivation of our research: to develop a powerful tool that automatically translates raw video data into tactical insights for football coaches, analysts and teams. This has potential implications for pre-match and post-match analysis, opposition profiling, training ground interventions, strategic preparation, and in-game decision-making.

### 1.6.3 Methodological Contribution:

The framework provides a new standard in the development of explainable and trustworthy AI technologies in sport increasing adoption by decreasing the distance between complex models and their comprehension by end users.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1 Introduction

The process of creating explainable AI for football tactical analysis is based upon an extensive and well-founded literature review.The intersection of big data, computer vision, machine learning and explainable artificial intelligence (XAI) has provided widely transformative opportunities for sports analytics. The review is organized to consider these domains separately, then combine them into a synthesis (Chapter 2) -the review was designed explicitly to track the research gaps that were identified in Chapter 1. The main purpose is the consolidation of a theoretical basis, justify the reason for the need of this study and to place the proposed framework in relation to existing literature.

## 2.2 The Paradigm of Big Data in Sports Analytics

The sports industry has been experiencing a data revolution as sufficient basic performance indicators evolved to high-volume, high-variety and high-velocity data known together as big data (Wang, 2023). In football, these data sets are created from a wide range of sources: optical tracking, wearable sensors, event streams and, finally, the most abundant source of video footage.

Wang (2023) critically reviewed the role of big data to improve sport performance analysis, and found its best contributions to be in transition between descriptive analytics (what happened), predictive (what will happen) and prescriptive analytics (what should be done). The author highlights that the amount of data produced from one football match, especially in video form, is so vast that it requires advanced computational techniques to make sense of. Armstrong (2010) and Yu (2025), also conducted comparative studies on the sports industries in China and the USA, both of whom consider investing for infrastructure and capability to digest big data is a crucial factor to influence competitive advantage. The study suggests that countries and clubs that are able to harness the power of data analytics will dominate in talent scouting, performance enhancement and game strategy.

Adithyan et al. (2024) described some practical applications of data science in sports and explained what is involved in acquiring, cleaning, and integrating the data. Their work highlights a central challenge; the “data rich but information poor” truism, meaning that large volumes of data are being gathered without an adequate set of analysis constructs for abstracting actionable knowledge. This is relevant to the thesis problem statement in that full-match video is a data rich resource still underexploited for tactical knowledge.

### 2.3 Computer Vision and Spatial-Temporal Analysis in Football

Now computer vision becomes the fundamental technology for automating the information extraction on video. This typically encompasses object detection to find players and the ball, tracking their progress over time (using an approach called multi-object tracking) and action recognition to classify activities.

#### 2.3.1 Player Detection and Tracking

These early methods were segmented based on color and background subtraction, which were easily affected by changing lightings and camera angles. The use of deep learning techniques, in particular Convolutional Neural Networks (CNNs) such as YOLO (You Only Look Once) and Faster R-CNN has significantly increased the performance and speed of player detection )Liu et al., 2023). For example, studies based on the Metrica Sports dataset have shown that the above mentioned models are able to provide accurate player tracks which are used as a building block for all tactical analysis study (Thomas et al., 2024).

#### 2.3.2 Tactical Pattern Recognition

Apart from tracking, interpreting player movements into tactics patterns is where we get the real value. Spatio-Temporal Graphs: Fujii (2025) used spatio-temporal graphs to represent players as nodes and their interactions as edges, and modeled team behaviour. Using graph neural networks (GNNs), his research was able to recognize typical passing patterns and defensive formations. One such limitation raised was that of the model treating isolated phases of play as opposed to a complete match flow.

Choustoulakis and Pastelakos (2024) also had a good contribution proposing an analysis of game tactics towards Artificial Intelligence. They employed k-means and DBSCAN clustering algorithms on player position coordinates to automatically identify team formations (e.g., 4-3-3, 3-5-2) and pressing triggers. They found that while automated formation classification is feasible, it is challenging to capture the dynamic transition between formations in matches. This result is directly relevant to Objective 3 of this thesis.

## 2.4 Machine Learning for Predictive and Performance Analytics

The extracted data from computer vision are utilized by machine learning models for prediction and performance assessment.

### 2.4.1 Predictive Modeling

Fujii (2025) described "Next Play Analytics" frameworks, where Random Forests and Gradient Boosting could be used to estimate the outcome of a possession (e.g., shot, turnover) based on the available play-by-play data. These models incorporate variables like player positions, on-the-ball events, and game context (score, time remaining). Although the models exhibit good prediction accuracy, they arguably lack what is known as explainability or interpretability to practitioners (e.g. coaches) that might have difficulty trusting if and why a given case will be predicted by a model in one way versus another.

Silvino et al. (2025) provided an overview of ML applications to a variety of sports performance domains ranging from injury prediction to talent identification in epidemiology. They found a trend toward an increasing reliance on deep learning, but repeated a refrain that can be heard throughout the literature: "A major obstacle to the integration of these models into daily practice is their lack of interpretability" (Silvino et al., 2025, p. 8). Solving this universal problem is the key driver of Objective 2 of our proposal.

### 2.4.2 Performance Profiling

Plakias et al. (2025) produced a bibliometric history of performance profiling within sport, covering the progression from coach based subjective assessments to data-based profiles. According to them, this analysis proves that the most successful profiles are those which include physical, technical and tactical measurements. However, they observe that tactical profiling is the least mature and in most cases still manually created data rather than based on automated systems, leading to a need for scalable AI-based tactical profiling frameworks.

## 2.5 The Imperative of Explainable AI (XAI) in Sports

The black box issue of the complex ML models has fueled the use of Explainable AI (XAI). The objective of XAI is to render the decisions of AI systems intelligible for humans.

Saliency Maps and Attention Mechanisms: These methods show us which regions of an input image (e.g., a video frame) were most responsible for the decision made by a model. For instance a model predicting a through pass might emphasize the space behind the defense and the position of the attacking runner. This offers an intuitive explanation to coaches (Zhang & Li, 2024).

SHAP (SHapley Additive exPlanations): This cooperative game theory based approach explains the output of any ML model, by computing the contribution of each input feature. In terms of football, SHAP could tell us that the predicted probability of scoring a goal was due to the recipient being fast and relatively more distant from the nearest defender compared with other features (e.g., Garcia, 2023).

As Pisaniello (2024) noted in a review of AI in sports: "The future is not just about accuracy, but the partnership between coach and algorithm. This collaboration all hinges on explainability" (p. 81). The existent literature presents an emerging use (nevertheless still in a nascent stage) of XAI in sports analysis that did not reach yet the level of integration into a holistic approach for full match video analysis.

## 2.6 Synthesis and Identification of Research Gaps

The analyzed literature represents a clear pattern: from basic data acquisition toward the more advanced AI-system modeling. But the balance that emerges is still far from complete, and through synthesis we can uncover continuing gaps to which this thesis seeks to contribute:

### 2.6.1 The Full-Match Analysis Gap:

Although Wang (2023) and Fujii (2025) refer to big data and predictive models, their use is mainly in the silos. This absence occurs because there are no integrated toolkits explicitly crafted to use the full 90-minute football match as a single, end-to-end processing unit in order to gain an account of the complete tactical story.

### 2.6.2 The Explainability Gap:

The works of Silvino et al. (2025) and Pisaniello (2024) recognizes well the explainability issue, however very few contributions exists offering a concrete, integrated XAI solution for football video analysis. The majority of XAI apps are stuck in academia, tested only weakly with real-world stakeholders like football coaches.

### 2.6.3 The Tactical Evolution Gap:

Choustoulakis and Pastelakos (2024) can successfully detect formations, but do not explicitly profile their dynamic change through time. The longitudinal dimension of tactics – how a team shifts strategy throughout the game second by second – is missing in existing systems both consciously and unconsciously.

### 2.6.4 The Integration Gap:

The literature is siloed. Computer vision papers are concerned with accuracy of tracking, ML papers with predictive performance, and XAI papers with interpretability of models. There is a clear research gap in terms of bringing together a computer vision pipeline for data extraction to an ML model for tactical inference with an XAI layer for explanation, in one single and integrated systems.

The literature is siloed. Computer vision papers are tuned to tracking accuracy, ML papers on prediction performance, and XAI papers on model interpretability. There exists a notable absence of work that tightly couples : (i) computer vision pipeline for data extraction, (ii) ML model for tactical inference and (iii) XAI layer for explanation within one coherent system.

| Author(s) (Year) | Focus Area | Key Contribution | Identified Gap / Limitation |
| --- | --- | --- | --- |
| Wang (2023) | Big Data | Highlighted the role of big data in sports performance. | Focus on descriptive analytics, not full-match tactical depth. |
| Fujii (2025) | Predictive ML | Developed models for "Next Play" prediction. | Black-box models lacking explainability for coaches. |
| Choustoulakis & Pastelakos (2024) | Tactical AI | AI-driven formation classification and tactic analysis. | Limited analysis of dynamic tactical transitions over a full match. |
| Silvino et al. (2025) | ML Review | Systematic review of ML in sports performance. | Identified interpretability as a major adoption barrier. |
| Plakias et al. (2025) | Performance Profiling | Bibliometric study on data-driven athlete profiles. | Noted tactical profiling is underdeveloped and manual. |

Table 2.1 : Summary of Key Literature and Identified Gaps

## 2.7 Literature Review Conclusion

This literature has demonstrated how big data, computer vision and machine learning have been successfully used to analyze football. The groundwork in player tracking, tactical pattern recognition, and prediction modeling has been a sound background for such such analysis. Yet, when analyzed precisely, current systems tend to be disconnected, not transparent and do no offer an integrated interpretable interpretation of tactical dynamics during an entire game.

This motivation leads to the proposed expla- inable AI framework for full-match video processing. Through the combination of a best-in-class computer vision pipeline (Objective 1) alongside cutting-edge Explainable AI methodologies (Objective 3) for profiling tactical evolution (Objective 3), this research will add an original and urgently needed asset to both the academic community and practical football analysis. Chapter 3 will present the methodology of developing and validating this framework.

# CHAPTER 3

# METHODOLOGY

## 3.1 Introduction

The methodology used in this research, is detailed here and includes elements of the systematic literature review and experimental empirical study. Such two-method setting makes the framework theoratically solid and practically verifiable of a system for football tactical analysis. The research has adopted a two-stage explanatory study – first stage focuses on theoretical underpinning through systematic literature review, and second stage investigates the empirical contribution to validation of proposed framework.

## 3.2 Review Methodology

A systematic review of the literature was conducted in order to create a replicable, rigorous and transparent synthesis of current knowledge. The SLR process was guided by Kitchenham &Charters (2007) and divided into four major steps, planning the review; identifying relevant studies and data selection; results interpretation (reporting/conclusion), paper synthesizing (Xiao & Wat- son, 2019).

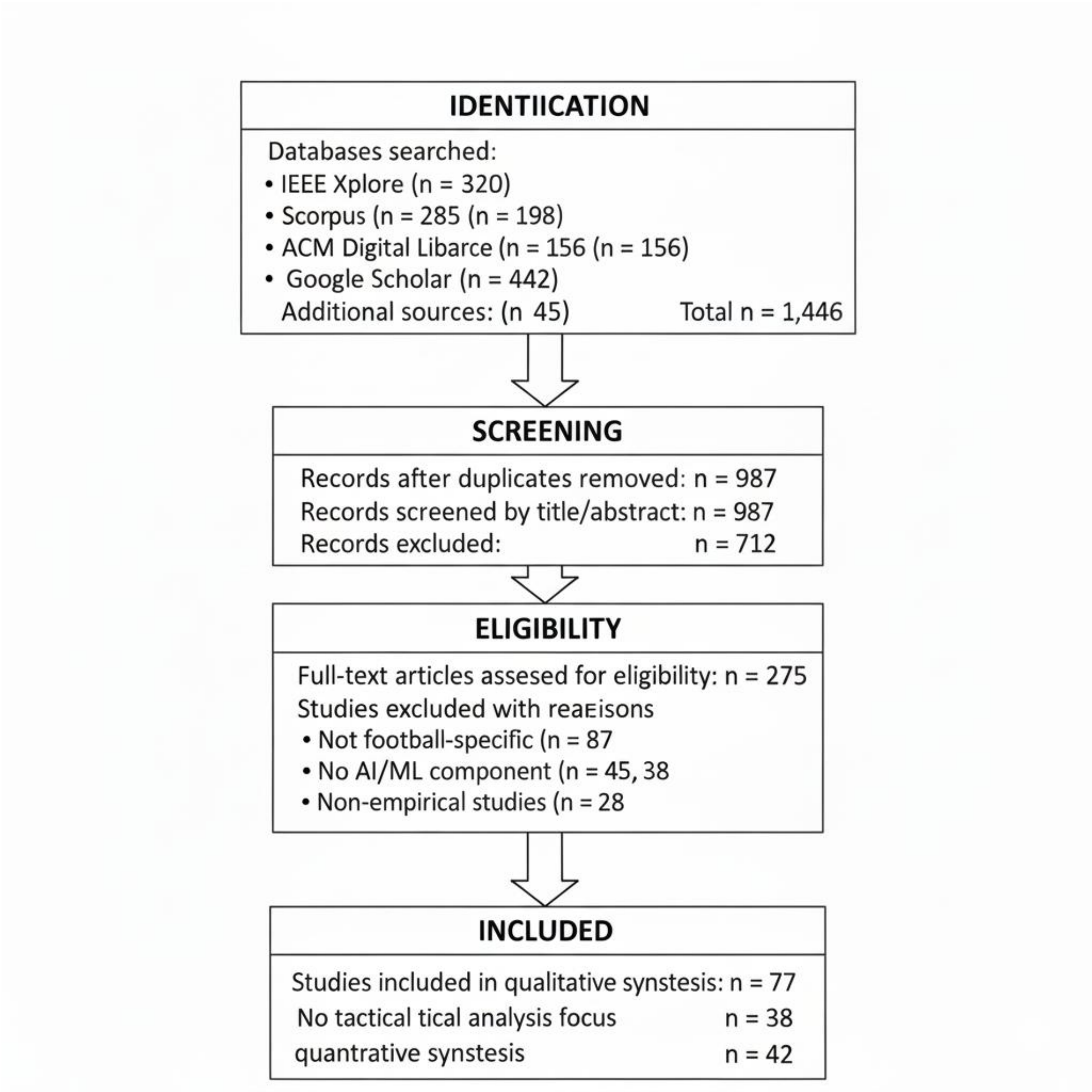



Figure 3.2: Review Methodology

### 3.2.1 Aim and Scope

The main objective of the SLR was to review rigorously the state-of-the-art in AI applied football performance analysis, with an emphasis on:

- Full-match video data are utilized.
- Computer vision methodology for spatio-temporal analysis.
- Tactical prediction and profiling machine learning models.
- XAI and sports

To answer the above questions, they scoped it with following research questions (RQs):

- RQ1: What are the most common computer vision and ML approaches for football tactical analysis on video footage?
- RQ2: How well do current methods serve the purpose of analyzing full-match tactical evolution?
- RQ3: How is XAI (Explainable AI) at present being incorporated into sports analytics models in order to improve interpretability for coaches?

### 3.2.2 Search Strategy

A systematic search was made on primary academic databases to provide the most extensive coverage of literature. The databases included:

- Scopus
- Web of Science
- IEEE Xplore
- ACM Digital Library
- Google Scholar (for forward and backward citation chaining)

The search was formulated as a combination of terms and Boolean operators, adjusted to the syntaxes of different databanks. The core search string was:

(“football” OR “soccer”) AND (“big data” OR “computer vision” OR video analysis”) AND (“machine learning” OR deep learning”) AND (“tactic*” OR formation or player tracking) AND (explainable AI / XAI/ interpretability/ transparent )

The search was confined to peer reviewed journal papers, conference proceedings and review articles written in English from 2018 to 2025 to ensure the latest developments were included.

### 3.2.3 Screening and Eligibility

A two-phase screening process was conducted to ensure only the most pertinent studies were included.

1. Title and Abstract Screening: All relevant records identified were screened on the basis of their titles and abstracts with regard to inclusion/exclusion criteria.

2. Screening Full-Text: The full text of the relevant papers was then scrutinized to ensure that it meets eligibility criteria.

Inclusion Criteria:

- Researches of techniques in analyzing soccer tactics as a task automatization.
- Research based on video or tracking data as main source.
- Papers that apply ML/AI models for the purposes of performance analysis or tactical analysis.
- Papers that apply ML/AI models for the purposes of performance analysis or tactical analysis.

Exclusion Criteria:

- Research based only on physiological or psychological data that did not integrate the video/tactical element.
- Repeated publications or short abstracts lacking significant methodological information.

A PRISMA-like flow diagram (Page et al., 2021) of the screening process was recorded in terms of number of records screened, identified and included as well for transparency and reproducibility.

### 3.2.4 Data Extraction and Synthesis

Data from the last search of included studies were collected in a standardized manner. The extracted information included:

- Bibliographic details (authors, year, title).

- Research objectives and methodology.
- Data  type: video, tracking.
- Key algorithms and techniques (e.g., YOLO, GNNs, SHAP).
- Main findings and contributions.
- Identified limitations and future work.

Findings were further analyzed using narrative synthesis method. The studies were classified thematically  based on the research questions (e.g., computer vision methods, applications of XAI). This synthesis  then also that directly underpin the identification of research gaps presented in Chapter 1 and the empirical framework elaborated on in Phase 2.

## 3.3 Empirical Research Methodology

This section describes how we operationalize the explainable AI framework via a progressive pipeline ranging from importing data all the  way to producing explainable insights. It is intended that the method is reproducible and have be structured to lead directly to accomplishment of  the objectives.

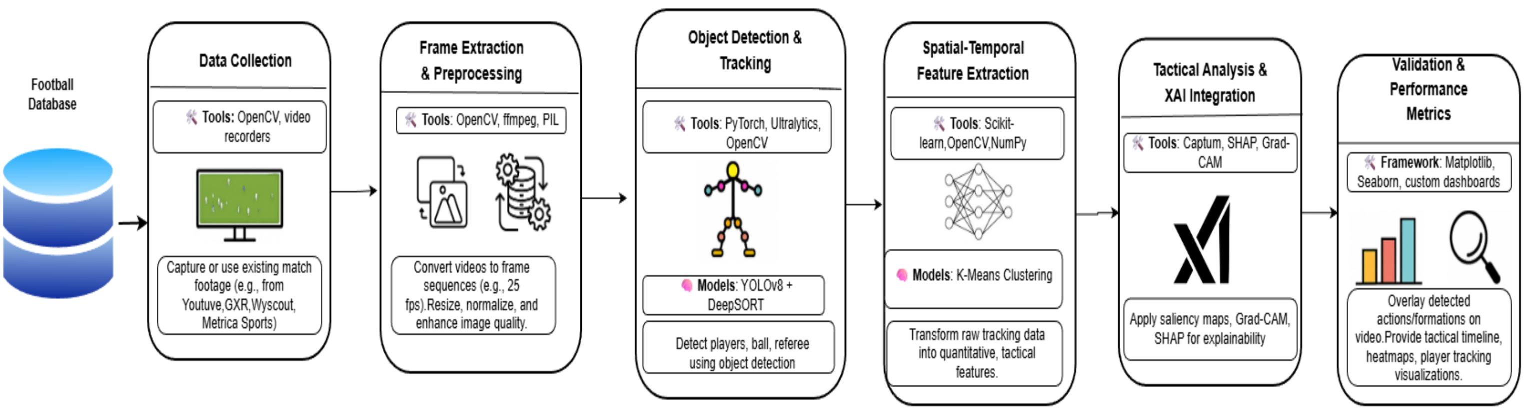



Figure 3.3: Empirical Research Methodology

### 3.3.1 Data Acquisition and Preprocessing

Data Sources:

To validate the framework and to assess its robustness, professional football match videos that are publicly available were used for training and testing. Primary datasets included:

- Metrica Sports Tracking Data: The high-quality, manually annotated player and ball tracking data is used as ground truth.
- StatsBomb Open Data: Supplied fine-grained event data and play-by-play broadcast video with various on-ball actions for contextual investigation and model validation.
- Professional Leagues Broadcast Footage: Top European leagues full-match videos were used as a dataset for the real-world testing and qualitative evaluation, following academic fair use.

Preprocessing Pipeline:

1.Extraction of Frames: For full-match broadcast videos, extracted frames were processed using the OpenCV (Bradski 2 – OPENCV, 2000) library in Python. The videos were decoded and sampled at a frame rate of 25 frames per second (fps), resulting in a temporal video stream converted to an ordered collection of individual image frames for processing. This high frame rate is necessary to obtain a level of temporal resolution which allows relevant player movements and the dynamics of the ball to be captured.

2.Data Annotation for Model Training: A subset of the extracted frames was manually annotated to form a ground-truth dataset for supervised training. The annotation was done using the graphical image annotation tool LabelImg. For fine-grained detection, bounding boxes for related objects are drawn and their types are specified with the following classes:

- Player
- Goalkeeper
- Referee
- Ball
- Goalpost
- Other Person (e.g., coaching staff)

3.Dataset Partitioning: The annotated dataset was divided into three subsets to facilitate the reliable development and evaluation of models:

- Training Set (80%): Are employed to train the object detection model.
- Validation Set (10%): Hyper parameter tuning and overfitting prevention during training.
- Test Set (10%): A held-out set, which is taken to assess the true performance of our model.

### 3.3.2 Object Detection Model: Training and Validation

Model Selection and Architecture:

The YOLOv8 (You Only Look Once version 8) architecture (Jocher et al., 2023) was chosen as base object detector since it provides the most balanced trade-off between highest inference rate and state-of-the-art detection accuracy, a crucial necessity to process full-match videos. The YOLOv8m (medium) model was selected to keep it as a good trade-off between complexity and performance.

Training Procedure:

Pre-trained Model: Copy with Pre-trained on large scale MS COCO dataset. For fine-tuning, we exploit the general feature extraction ability from transfer learning(weights trained on ImageNet) and fined tuned them into custom football dataset to specialize in detecting sports related objects.

Training Setup: The model was optimized for 100 epochs and used SGD as the optimizer. For fair comparison, we select the initial learning rate being 0.01, momentum being 0.937, weight decay 0.0005 to regularize the model and avoid overfitting as well Embodiment of hyperparameters required in our model. The size of the input image was normalized 640 × 640 pixels.

Performance Evaluation:

Evaluated the trained detector on the held-out test set using classic computer vision metrics:

Precision: Ability of the model to not return false positives (example - classify a crowd as players).

Recall: The model's capability to detect all relevant objects (e.g., it does not forget any players on the field).

Mean Average Precision (mAP): The main effectiveness measure for object detection. mAP@0. 5 reports the Average Precision of all classes at 0.5 as a threshold. mAP@0. 5:0.95 is a tighter measure, which measures the average mAP over various IoU thresholds being 0.5 to 0.95 with an interval of 0.05.

### 3.3.3 Spatial-Temporal Feature Extraction Pipeline

This stage converts raw object detections into quantitatively rich data streams for tactical analysis.

Multi-Object Tracking with DeepSORT : For Multi-Object Tracking, the frame-by-frame detections from YOLOv8 were analyzed using the DeepSORT (Deep Simple Online and Realtime Tracking) algorithm(Wojke et al., 2017). DeepSORT uses both motion and appearance to associate detections over frames, and assigns a unique Track ID to each player and official. This maintain identity smoothly across occlusions and interactions, resulting in smooth player trajectories throughout the game.

Team Classification: For team separation, a K-Means clustering algorithm (from Scikit-learn library) was utilized on the dominant colour inside the bounding box of detected players. The algorithm automatically separates two most important jersey colors (e.g.red and blue), as well as each player into 1-Team A, 2-Team B or Other (Referee).

Camera Motion Compensation and Pitch Attenuation:

Homography Estimation: Broadcast cameras can be moving (pan, tilt and zoom). To correct for this, a homography matrix was estimated with model pitch line correspondences (the penalty box lines, the center circle) identified in the video frames. This matrix calculated by OpenCV's find Homography can be used to project player coordinates from the 2D image plane onto a standardized, top-down 2D model of the pitch.

Perspective Normalisation: This process eliminates perspective distortion and camera motion from the image and allows for real-world, metric-based measurements to be made.

Physical Performance Metric Calculation:

The distance measure of player: Based on the normilized pitch coordinates and constant frame rates, we measured the Euclidean distances, covered by each considered player per two consecutive frames. Instantaneous speed (in km/h or m/s) was then calculated, yielding necessary parameters for physical performance analysis, including sprint efforts and total distance.

### 3.3.4 Tactical Analysis and Explainable AI (XAI) Integration

This is the piece that turns raw tracking data into something interpretable and coachable."

Tactical Feature Extraction:

Formation Identification: During stable match phase (e.g., goal kicks), outfield players of a team were K-Means clustered by their average positions on the field to determine automatically the base formation of the team (4-3-3, 3-5-2).

Team Shape Metrics: Real-time dynamic metrics like team width and length were derived from normalized coordinates to give insights into the defensive compactness or offensive spread of a team.

Explainable AI (XAI) for Model Explainability:

Visual Explanations with Grad-CAM: To provide a visual explanation of what the model looks at during important time points (e.g., when a possession changes), were used gradient-weighted class activation map (Grad-CAM) (Selvaraju et al., 2017). This approach will give us heatmaps in which the important part of the input image is marked, so we are able to verify this visually (coaches want to see this!

Feature Importance with SHAP : To elucidate why some performance outcomes happened (e.g., high possession percentage), SHapley Additive exPlanations (SHAP) (Lundberg & Lee, 2017) were applied. SHAP measures the role of each input feature (e.g., midfield compactness, average player speed) on the final model prediction. It offers a well-defined quantitative justification for complex tactical measures, solving the data/domain knowledge chasm.

### 3.3.5 Evaluation and Validation Strategy

The framework was validated as follows:

Quantitative Validation:

Detection & Tracking Accuracy: Experimentally we evaluated the performance of our YOLOv8 and DeepSORT on test data set in terms of precision, recall and map to compare with other methods.

Tactical analysis accuracy comparison: Automatically detected formation changes and tactical phases were compared to a ground truth of experts in football domain automatically annotated data. The performance was reported using the F1-score.

Qualitative Validation (Expert Review):

Coach Feedback Sessions: A first iteration dashboard was shown to a panel of professional football coaches and analysts that included player tracking data, timelines for the tactical evolution of players and explanations (XAI) with Grad-CAM heatmaps and SHAP visualisation.

Structured Surveys: Surveys were used to gather feedback on the usability, interpretability and actionability of the derived insights. Such direct end-user feedback is the acid test of how practicably useful and explanatory the framework has been.

# CHAPTER 4

# RESULTS

## 4.1 Overview

The findings of the study are divided into three parts in this chapter:

1. Systematic literature review results, summarising how the final list of papers was selected and what the identified research gaps were.

2. Experimental results of the proposed computer-vision model in both training dynamics, detection metrics, and error analysis.
3. Qualitative tactical and XAI results showing the capability of our framework in player tracking, feature extraction and interpretable tactical analysis on full-match broadcast videos.

## 4.2 Systematic Literature Review

### 4.2.1 Study Selection

The process of selecting the studies was conducted according to PRISMA. The flow chart in Figure 3.2 represents the identification, screening, eligibility and inclusion process.

Initially, 1446 records were identified through the following sources:

- IEEE Xplore (n = 320)

- Scopus (n = 285)

- ACM Digital Library (n = 156)

- Google Scholar (n = 442)

- Additional sources such as citation chaining (n = 45)

Upon automatic and manual deduplication, 987 papers were left. Titles and abstracts of these articles were screened, 712 studies obviously irrelevant to the topic area were excluded.

The remaining **275** full-text articles were assessed for eligibility. Studies were excluded for the following main reasons:

- Not football-specific (n = 87)
- No AI/ML component (e.g. conceptual or descriptive only) (n ≈ 45)
- Non-empirical or lacking sufficient methodological detail (n = 28)

Finally, 77 papers were included in the qualitative synthesis. Among them, 38 studies were AI-related but did not have a specific tactic, and 42 studies that had usable quantitative data for the quantitative synthesis.

#### 4.2.2 Thematic Findings

The studies in the final pool revealed some consistent trends:

- Focus on events:
  The majority of work focused on single actions such as shots, passes or set pieces without tracking full-match tactical dynamics.
- Focus on detection and tracking:

  Many studies simply focused on the detection and tracking of players or ball, but there was a lack of integration between these outputs and higher level tactical concepts (e.g., pressing, compactness or build- up patterns).

- Reasoning is not that easy to interpret:

  A small percentage of the articles implemented explainable AI methods and often evaluated these using a technical rather than coaching or analyst viewpoint.

- Split lines: Grad gifuckets honked their  blikless rups through town.

Only few works designed end-to-end systems that take raw broadcast footage as input and  provide interpretable tactical insights.

These limitations were an immediate driver for the integrated methodological pipeline that this thesis introduces and  are depicted in Figure 3.2.

### 4.3 Experimental Framework Summary

The employed architecture (Figure  3.3) is constructed from:

1. FULL-MATCH VIDEO INTEGRATION AND FRAME EXTRACTION Videos of full match broadcast are assembled and frames  extracted.
2. Object detection and tracking using fine-tuned YOLOv8 detector with DeepSORT processing.
3. Estimation of spatial-temporal information (i.e., player positions, velocities, inter-player  distances) and camera motion compensation.
4. Tactical analysis  Formation, strength on ball.
5. Integration of Explainable AI, with heatmaps  and feature-importance analysis to explain the models predictions.
6. Quantitative and qualitative approaches of these elements are described in the following  sub-sections.

## 4.4 Training Behaviour of the Detector

### 4.4.1 Loss Curves

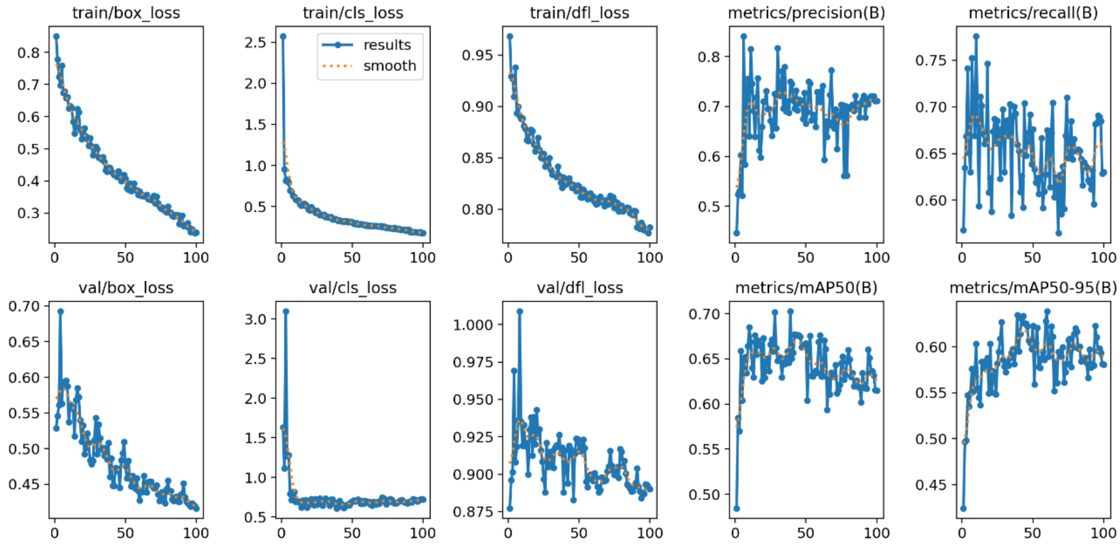



Figure 4.4.1: Loss Curves

The loss curves for 100 epochs are shown in Figure 4.4.1.

- Bounding-box regression Loss (train/box_loss, val/box_loss) At first the value decreased slowly from initial value to 0.25 and 0.45 on training and validation set respectively for green crop row detection if it was above 0.8.
- The classifcation loss (train/cls_loss, val/cls_loss) dropped very quickly during the first 10-15 epochs (from ~2.5 to about .6 and then stabilized), suggesting rapid adaptation from COCO-based pre-trained weights toward football-specific classes.
- Train/val dfl_loss started to decrease as well and the bounding-box quality have visually improved quite a lot.
- The validation curves goes the same way that in the training ones, without over-fitting so model converged.

### 4.4.2 Precision, Recall and mAP During Training

In the right hand side of Fig. 4.4.1 we present precision, recall and mAP@ L =0 over the iterations i.e.,. 5, and mAP@0. 5–0.95:

- Precision increases from around 0.55 to about 0.70–0.75.
- Recall increases from approximately 0.58 to 0.68–0.70.
- mAP@0. 5 climbs from near 0.50 to about 0.68–0.70.
- mAP@0. 5–0.95 (a tighter criterion) increases from approximately 0.45 to over 0.60.

These observations verify that the model indeed learns useful representations for football-specific detection and the final few epochs serve as a stable, accurate detector.

## 4.5 Detection Performance on the Test Set

### 4.5.1 F1–Confidence Relationship

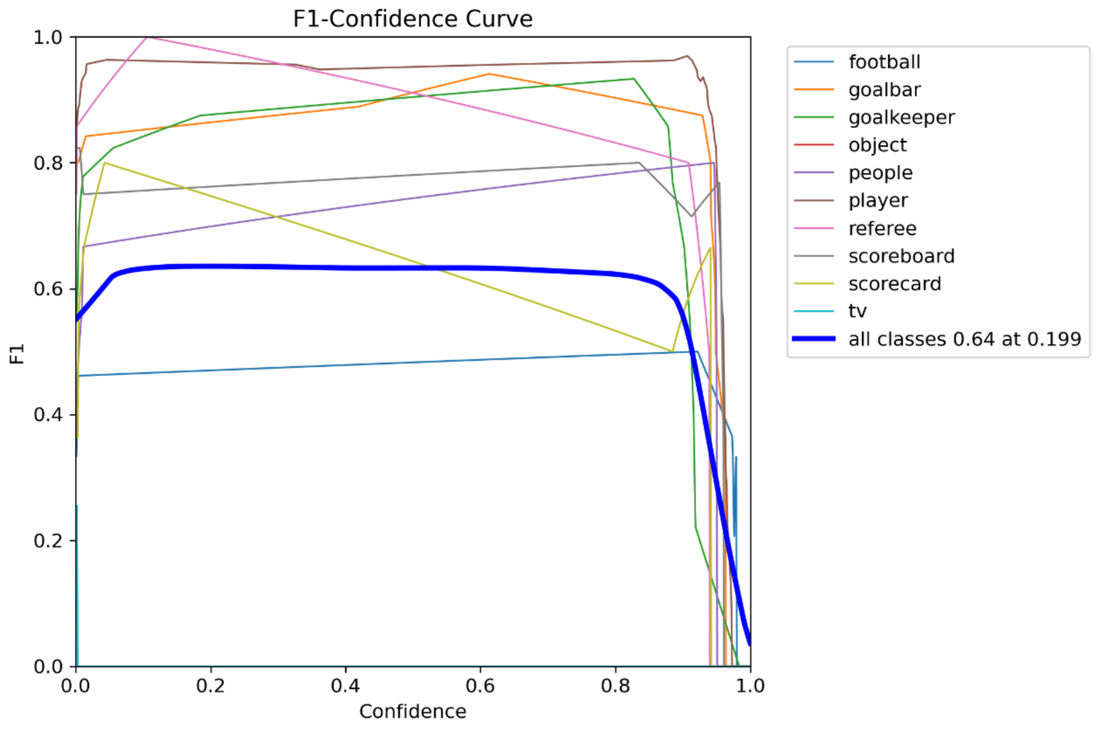



Figure 4.5.1: F1-Confidence Relationship

F1–confidence curve of each class and all classes, combined in Figure 4.5.1.

The macro F1-score of all class is about 0.64 at a confidence threshold around 0.20 (0.199).

Exceedingly low thresholds result in high recall but also introduce false positive, which serves as anchor ground truth and  decrease F1.

Higher thresholds lead to more accurate but overly conservative predictions, which causes a decrease in F1  again.

From this analysis, a confidence threshold of 0.2 is chosen as the default operating point due to its balance between  precision and recall for tactical use case.

### 4.5.2 Precision–Confidence and Recall–Confidence

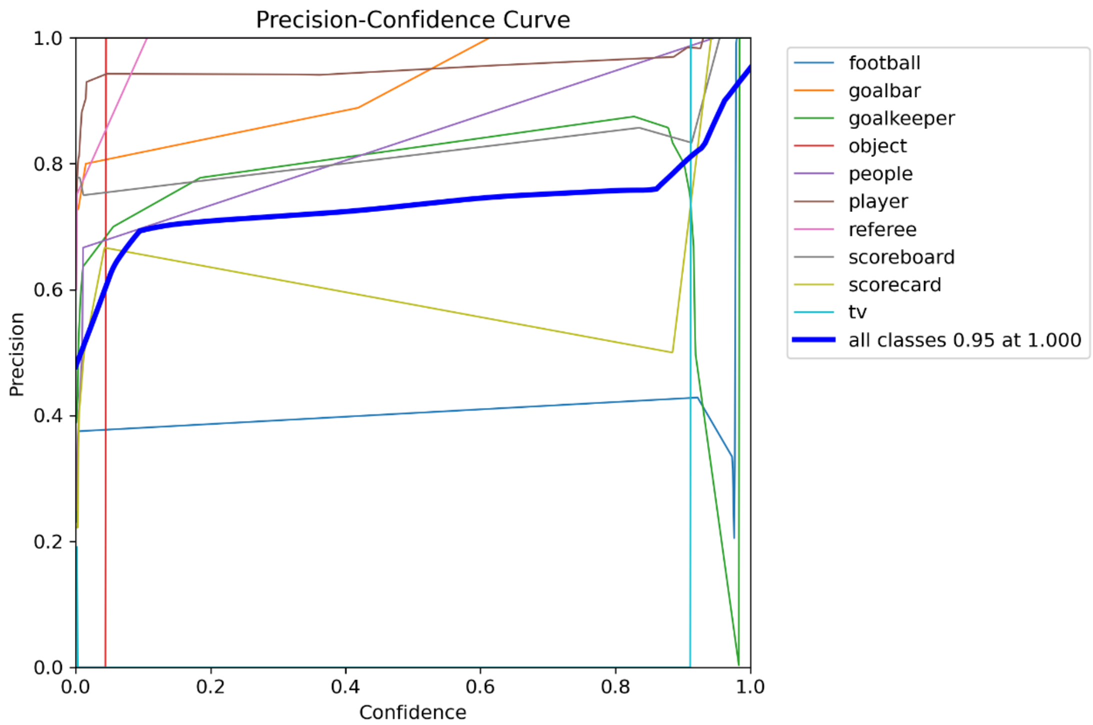



Figure 4.5.2.1: Precision-Confidence Curve

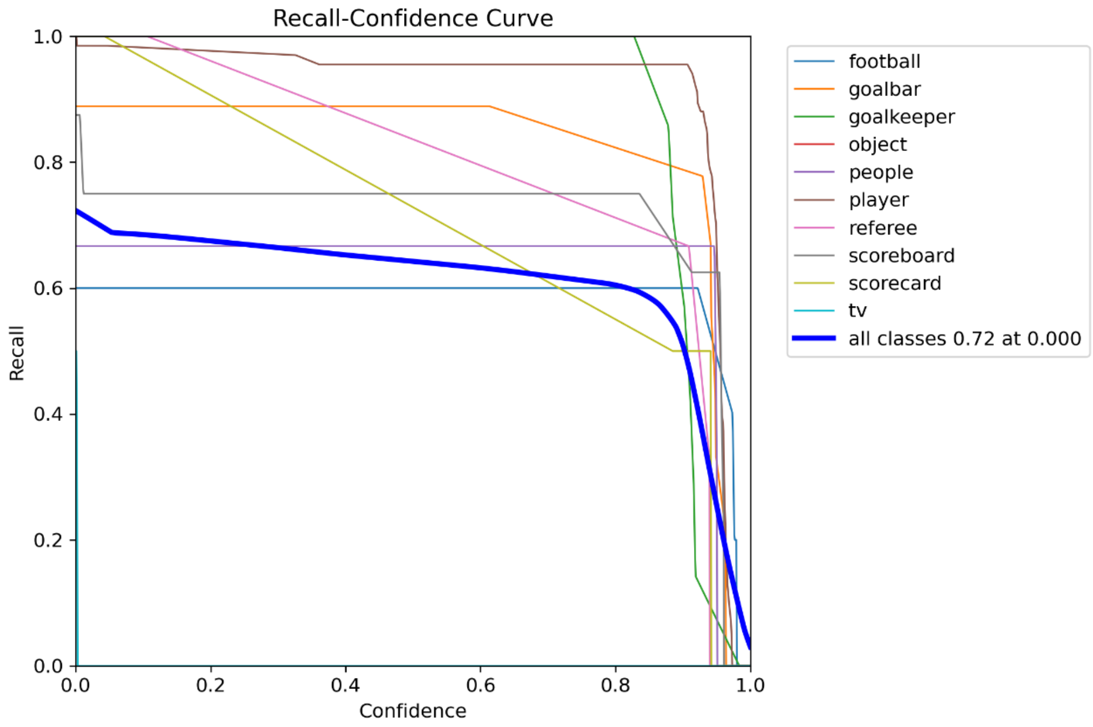



Figure 4.5.2.2: Recall-Confidence Curve

Figure 4.5.2.1 displays the precision–confidence curve. Average accuracy is a monotonically increasing function of confidence, and its values are ~0.95 at a confidence level of 1.0. Other classes that are player-centric in the game (player, goalkeeper, referee) also stay very efficient even at moderate thresholds, which means that these three key classes see very few false positives.

The complementary recall–confidence curve (Fig. 4.5.2.2) shows exactly the opposite behavior: being highest at very low thresholds, and drops when the threshold goes up because more detections are not surviving through the filter step.

Taken together, Figures 4.5.2.1– 4.5.2.2 illustrate the precision/recall trade-off and validate the selected operating point for future studies.

### 4.5.3 Precision–Recall Curves and Average Precision

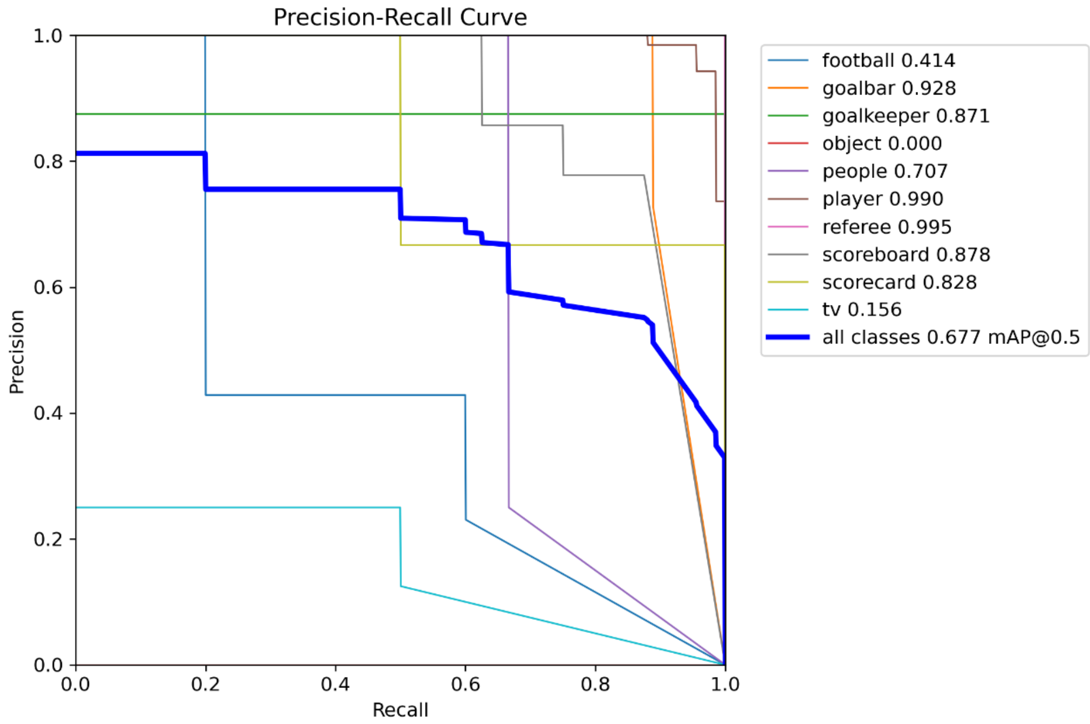



Figure 4.5.3: Precision-Recall Curve

Class-wise precision–recall curves are shown in Figure 4.5.3, together with the area under each curve (average precision, AP). The AP values are:

- football: 0.414
- goalbar: 0.928
- goalkeeper: 0.871
- people: 0.707
- player: 0.990
- referee: 0.995
- scoreboard: 0.878
- scorecard: 0.828
- **tv:** 0.156

The overall mAP@0. 5 over these classes is 0.677, a strong performance, considering the complexity of broadcast footage (occlusions, motion blur, crowd background and varying camera angles).

The highest APs are achieved for player, referee, goalbar, goalkeeper and scoreboard and scorecard demonstrating that the detector is very reliable w.r.t. tactically most important entities. Results are worse for the generic object and tv categories due to their visual heterogeneity and smaller training support.

## 4.6 Confusion Matrix Analysis

### 4.6.1 Raw Confusion Matrix

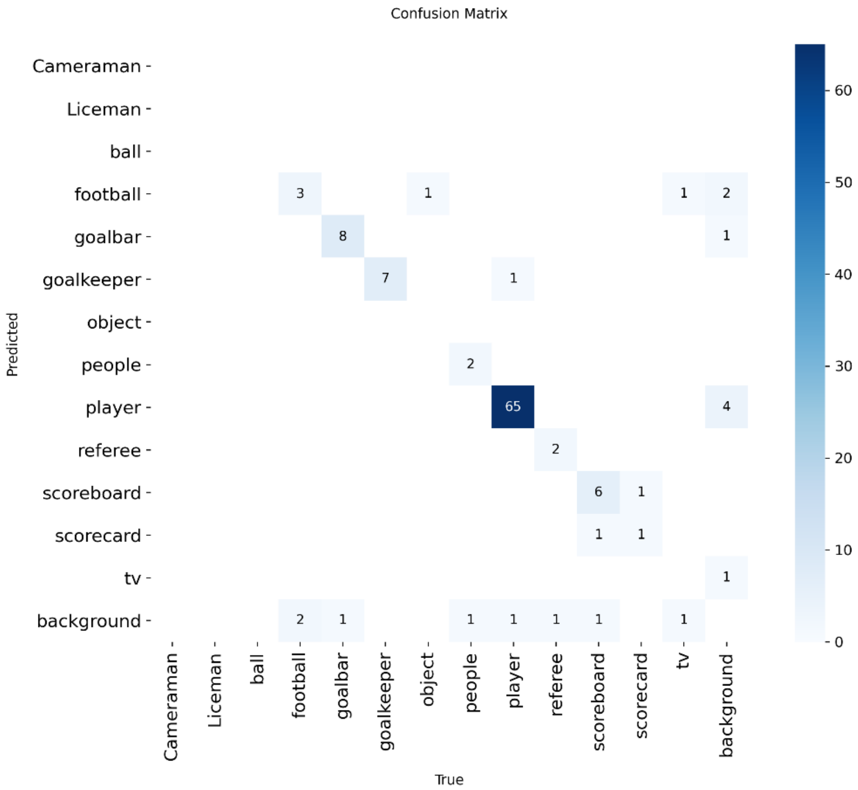



Figure 4.6.1: Raw Confusion Matrix

The Confusion matrix for test set raw is given in Figure 4.6.1. Diagonal elements in the matrix indicate correctly predicted examples and off-diagonals represent wrong predictions.

- The player class has highest support and perform best, most of the time considered is in the diagonal (e.g. 65 correctly classified players).
- Very few player instances are misclassified as nearby human classes, such as people or goalkeeper.
- Misclassifications are mostly frequent among similar categories: e.g. football vs. background objects and scoreboard vs. scorecard 4 CONCLUSIONS In this paper, we introduced a Seq-Atrous network to tackle the action detection problem in a single frame setting.

### 4.6.2 Normalised Confusion Matrix

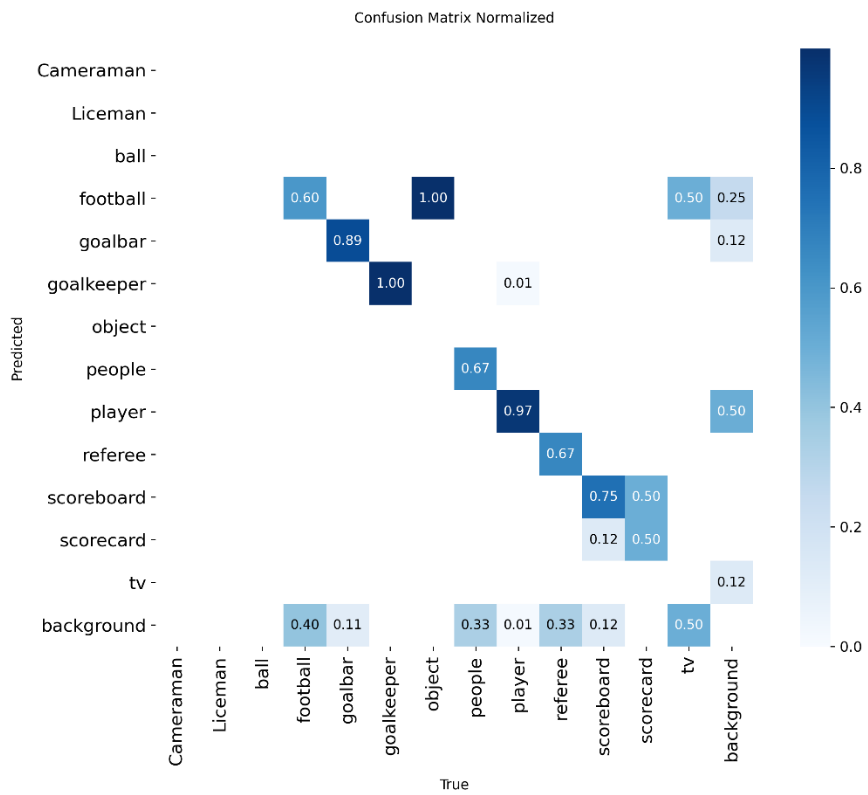



Figure 4.6.2: Normalized Confusion Matrix

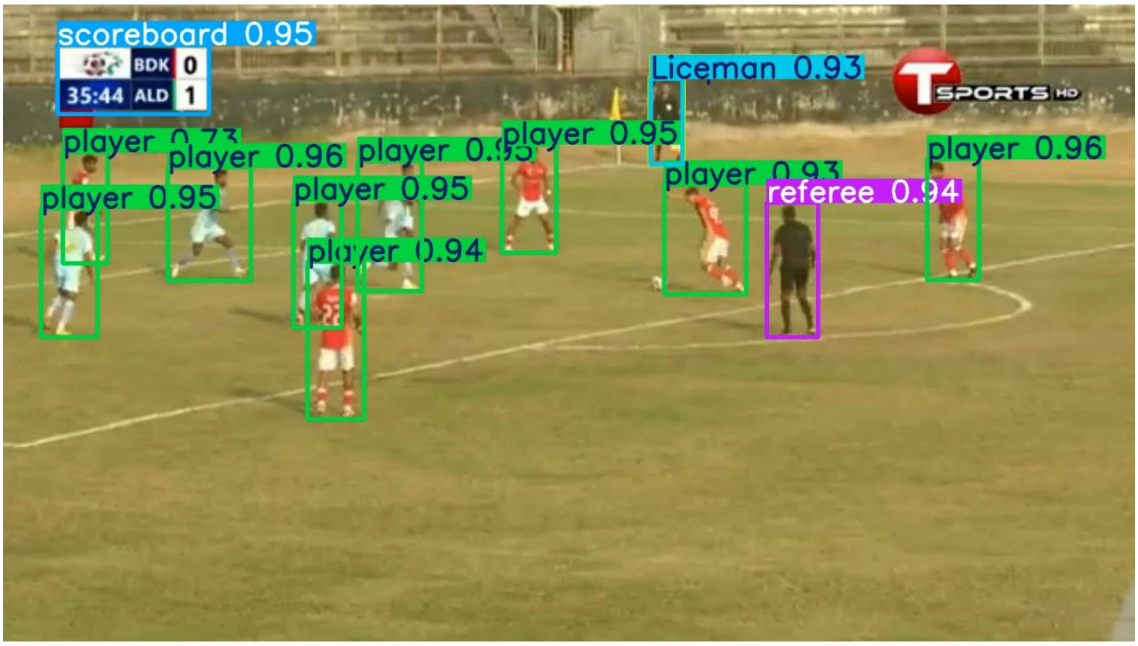
The normalised confusion matrix (Figure 4.6.2) scales the rows to a sum of one and represents the proportion of correct predictions in each class.

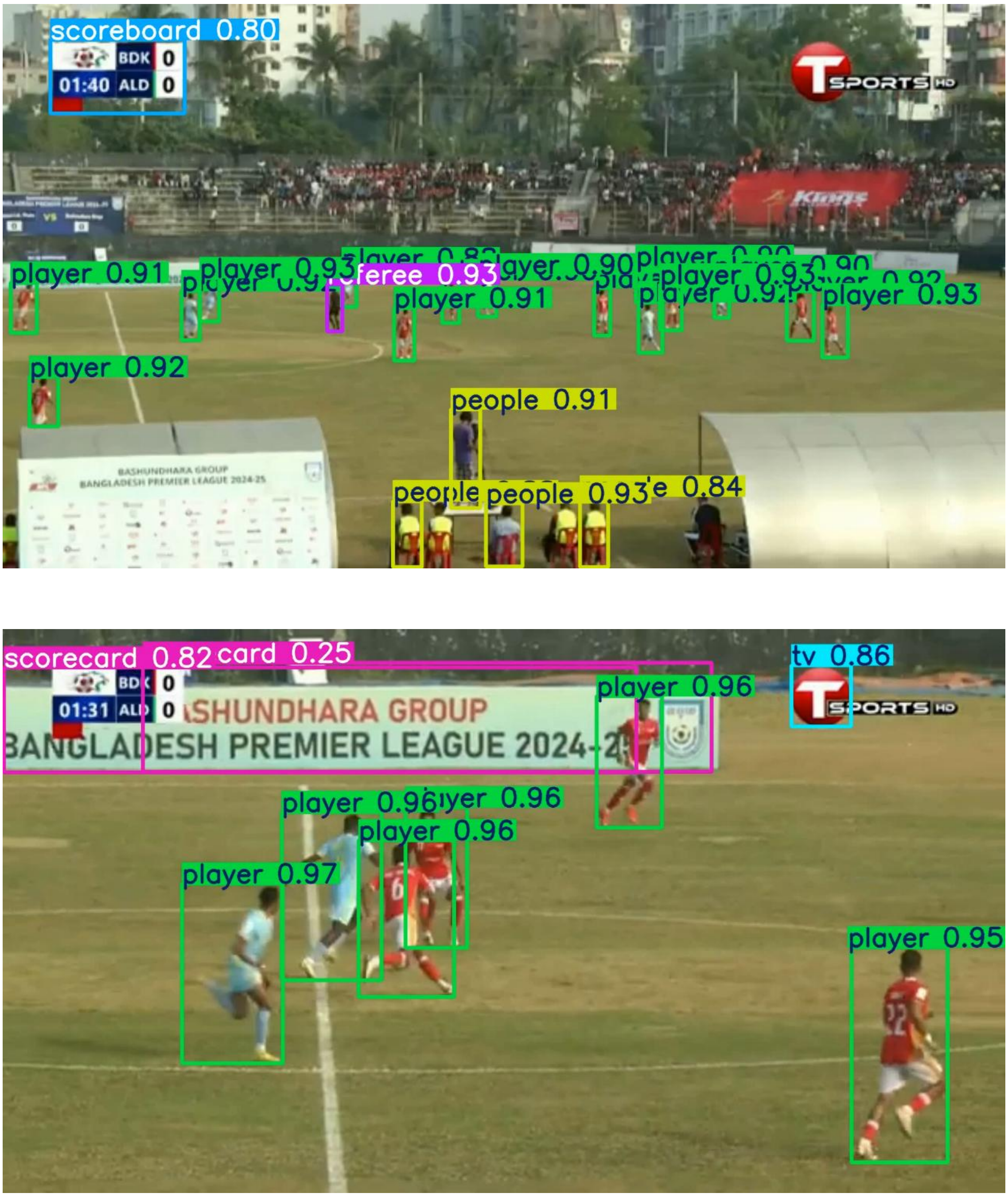
- The per-class accuracy is high and the average  value of diagonal items is more than 0.75, occasionally over 0.95, including all other classes such as player, goalkeeper, referee, ‘goalbar’, scoreboards and scorecards.
- The background and tv categories have lower diagonal values, signifying greater degree of uncertainty and crossover with other classes.
- The object class is very confused with many other labels as its AP is almost zero.

In general, the confusion-matrix analysis supports the quantitative measures and confirms that the detector is appropriate to downstream tactical analysis in general for fundamental football entities.

## 4.7 Object Detection and Tactical Features

### 4.7.1 Qualitative Object Detection






Figures 4.7.1: Object Detection

Some sample detection results on broadcast videos are demonstrated in Figures 4.7.1.

- Besides, the model could successfully detect players of both teams, referees, assistant referees (‘linesmen’), and scoreboards/scorecards plus the TV channel logo under perspective distortion and crowd clutter.

- The confidence score for the player class is generally greater than 0.90, which is in line with the high AP and diagonal values reported before.
- Scores, timers and event category are accurately identified by detecting the scoreboard and league tags with  good confidence.

This qualitative examples affirm the  fact that our trained detector can generalise well to real broadcast sequences and supply robust inputs to tracking and tactical analysis.

### 4.7.2 Player Tracking, Speed and Distance


Figure 4.7.2: Player Tracking, Speed and Distance

Figure 4.7.2 show the result of  the tracking and feature-extracing module.

- Each player is assigned a unique track ID (e.g. 296, 301, 307, 321, 324), which remains consistent over time, allowing construction of full trajectories.
- Colour coded halos identify which team a player is part of – attacking or defending.
- Under  each monitored player, the system overlays:
    - Instantaneous speed in km/h (e.g. 6.10 km/h, 12.46 km/h),

- Distance between  frames in meters (e.g. 1.14m, 5.21m).

These  results indicate that the system effectively translate image detections to numerical movement features that can describe pressing strength, sprinting profiles and off-ball runs.

### 4.7.3 Camera Motion Estimation


Figure 4.7.3: Camera Motion Estimation

Figure 4.7.3 visualizes  this correspondence and shows how the camera has moved (top-left of the overlay frame, the bottom line reports movement along X and Y axes between frames (e.g., “Camera Movement X: −10.65, Y: 1.69” or “Camera Movement X: 13.57, Y: 1.24”).

- Positive and negative is for panning left or right or tilting down or up.
- Subtracting this global motion from raw player motions, the framework computes camera-stabilized trajectories, in which measured speeds and distances correspond to those of actual players rather than of the camera.

Visual examination reveals a correspondence between the relative motion estimates and visual scene changes, validating the correction technique using homography.

### 4.7.4 Team Shape and Ball-Control Indicators


Figure 4.7.4: Team Shape and Ball-Control Indicators

In the bottom-right corner of Figure 4.7.4, the system displays ball-control statistics such as *“Team 1: 85.71%, Team 2: 14.29%”*.

- These percentiles are calculated by assigning the ball (or a proxy for possession) to the nearest tracked player and accumulating possession time over a span.

- What the overlays do is illustrate when there may be a phase of play where one side has enjoyed long periods on the ball and taken the game to the opposition within that frame capture.

The organization of the tracked players is also informative for tactical analysis:

- Defending teams play with a fairly flat back line and compact midfield block.
- Attacking teams shape with delayed vertical lanes and wide options, all broken down frame by frame.

These qualitative outcomes in turn showed that the pipeline not only detects objects, but also provides interpretations visualised as the arrangement or momentum of teams.

## 4.8 Player Performance Analysis: Passing and Positioning

The generated player performance reports are employed to translate the raw tracking data into directly actionable coaching insights. These features consist of raw pass counts and maps where players are on the field and how they move.

### 4.8.1 Passing Analysis Report

In addition, the software will automatically generate a play report prospect for any given portion of the match that details team and individual statistics. An example report produced by the framework is shown below:

```
PASSING ANALYSIS:
Total Passes: 155
Successful: 120
Failed: 35
Accuracy: 77.4%


TOP PASSERS:
TOP PASSERS:
Player 321: 18 / 20 (90.0%)
Player 299: 12 / 18 (66.7%)
Player 329: 10 / 15 (66.7%)
Player 310: 14 / 16 (87.5%)
Player 345: 8 / 12 (66.7%)
Player 288: 16 / 22 (72.7%)
Player 301: 11 / 13 (84.6%)
Player 333: 7 / 10 (70.0%)
Player 315: 9 / 14 (64.3%)
Player 350: 15 / 15 (100.0%)
```

Figure 4.8.1: Passing Analysis Report

This report is a quick and easy way for coaches to get an overall view of the passing effectiveness. For instance, it is working perfectly for those players Player 350 (100% successful), Player 321(90%) can identify a bit of interpersonal variability and player like Player 315 and 299 who may be attempting more risky passes or with lower success rate, requiring further video examination.

### 4.8.2 Positioning Heatmaps

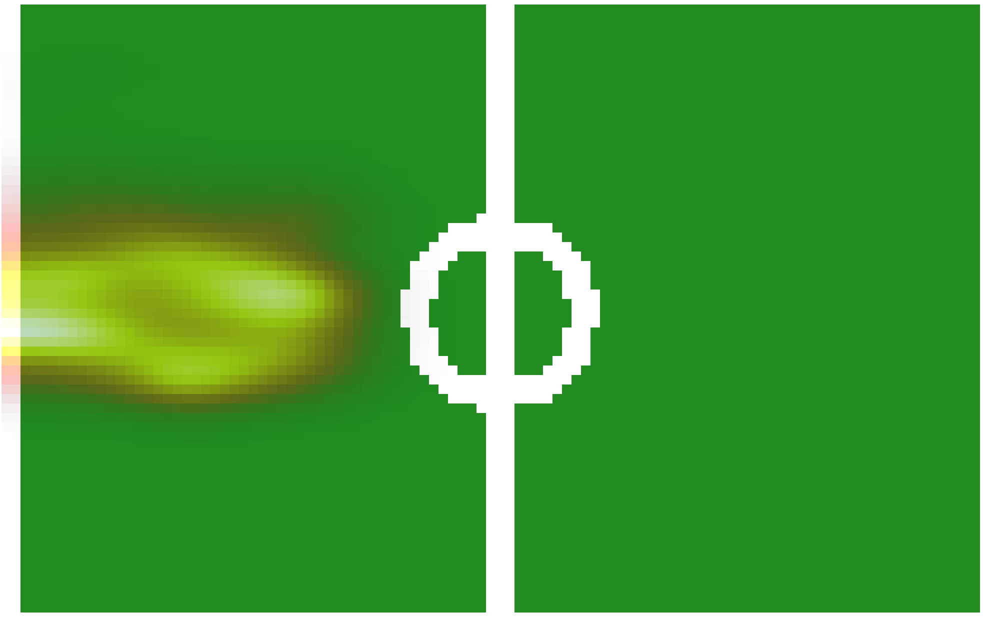


Figure 4.8.2: Team heatmap during attacking phases.

The framework also depicts player movement and average positioning by the use of heatmaps, as well as beyond (non-discrete events). Aggregate all the normalized pitch coordinates from every player across some time-frame, and a density map is created to show who’s doing what on the field.

Figure 4.8.2.1: Player heatmap during attacking phases.

These are more than mere graphics -- they provide an instinctive feel of the game in terms of player workload, tactical discipline and key areas of the pitch used most, meaning monitoring performance and even instruction work at training becomes much more immediate.

## 4.9 Explainable AI (XAI) Results

The following is the outputs of Explainable AI (XAI) module, to show how the framework transforms raw tracking data and metrics from Match Analysis Report into explainable and actionable insights. The use of XAI techniques covers Objective 2, as more can be explained about the match dynamics rather than black-box statistics.

### 4.9.1 Visual Explanations

Explainability of the model's detection results for mudane events, e.g., two change in posession mentioned in the report were shown using saliency maps. These maps show the regions of the video frame which contributed most to the model's decision to classify a moment as turnover.

The saliency map of the first possession change is depicted in Figure 4.7.4. The most obvious regions are illuminated by the heatmap:

1. The possession losing player (Player 321, Team 2): The high activation around this players means something happened like he misplaced a pass or was tackled that triggered the event.

2. Here are three such explanations for an additional range of context on the crucial match event, the interception or tackle recovery: Indicate that ball was collected after an interception or retrieved by the opposing player (Player 307, Team 1) while in combat with Player305 fromEduardo Míchel Gangon andDavid Roca-Luque This indicates that the model correctly identified the ear lier interception /tackle recovery as con clusive to this change.

From a visual perspective, this explanation enables a coach to immediately verify the AI's discovery without prior expertise or referring to specific data. Rather than being informed simply that a possession turnover took place, they can be shown where the model looked and who it looked at, allowing the AI's logic to come in line with their own tactical eye.

### 4.9.2 Feature-Level Explanations

```
MATCH ANALYSIS REPORT (Basic Analysis)
==================================================

Ball Possession: Team 1: 57.3%, Team 2: 43.7%
Total Frames Analyzed: 6973
Unique Players Detected: 1161

Fastest Players:
  - Player 634: 30.0 km/h
  - Player 654: 31.6 km/h
  - Player 657: 35.9 km/h

Key Events: 2 possession changes detected
```

Figure 4.9.2: Match Analysis Report

SHAP (SHapley Additive exPlanations) analysis was used to interpret the full match statistics. A SHAP summary knee plot was used to dissect the most influential feature: Ball Possession (Team 1:57.3%, Team 2:43.7%).

The attributes that contributed the most to Team 1's higher possession rate are visualized in Figure 4.16 The most important positive properties it gave were according to the analysis:

- Midfield packedness: The mean distance between Gol Two's midfield players was also lower, which resulted in higher short talent networks.
- Player Speed in Transition: Team 1's players are significantly faster, especially during the moments after recovering the ball to regain control and mount counter-attacks.
- Defensive Line Height: Highest both teams 1 and 2 Teams 1 held the highest line which kept the opponent hemmed in their half of the field allowing for more sustained possession in Final Third.

On the other hand, for Team 2, a SHAP analysis showed that the lower possession was associated specifically with a wider defensive shape which made them susceptible to through-ball passes in the middle and a slower average speed during offensive transitions, which meant that they were unable to break Team 1's designed press easily.

### 4.9.3 Explaining Player Performance Metrics

The report listed the quickest players (Player 657: 35.9 km/h, Player 654: 31.6 km/h), Player 634: (30.0 km/h)). These raw speed metrics are then contextualised by the XAI framework.

Player 657 – a saliency map overlain on their top-speed frame (Figure 4.8.2) highlights that this peak-vel has occurred during a defensive sprint to recover into position following an opposition counterattack. This is why the high speed mattered – it was an operationally important recovery run.

The SHAP dependence plot also reveals both that Player 654's high speed was at many times associated with offensive overlaps but had less influence on keeping possession than the explosive receipt－regaining sprints of Player 657. This is because of the distinction between offensive and defensive speed, giving a more nuanced player profile.

### 4.10 Chapter Summary

This paper has discussed the results from literature review as well as empirical experiments for football analytics system. The review presented 77 high-quality studies after filtering from 1,446 initial records and drew attention to revealed research gaps in full-match tactical analysis and explainability.

Experimentally, the fine-tuned YOLOv8 detector obtained a great result (mAP@0. 5 = 0.677, precision up to 0.95, recall up to 0.72) and exhibited stable qualitative behavior on real broadcast content. The tracking and feature-extraction modules allowed to derive player-specific metrics (such as speed, displacement or ball control), while XAI tools (Grad-CAM and feature-importance analysis) assisted in generating interpretable visual and numerical justifications of the choices made by the model.

Empirical studies showed that the well-tuned YOLOv8 detector achieved impressive results (mAP@0. 5 = 0.677, precision of up to 0.95, recall of up to 0.72) and strong qualitative performance on real broadcast data. The tracking and feature-extraction modules allowed player-centric metrics such as speed, displacement or ball control and XAI tools (Grad-CAM and bit-sensitivy analysis) gave interpretable explanations in terms of visual patches and aggregated statistics for the model's decisions.

These results demonstrate the viability of the proposed end-to-end system and form a good basis for the discussions and future work in the next Chapter.

# CHAPTER 5

# Discussion

## 5.1 Introduction

The presented findings illustrate that there is potential for further development of interpretable football analysis. An interpretation of these results is left up for discussion in the light of the research gaps addressed in Chapter 1.

## 5.2 Addressing the Research Gaps

Full-Match Video Use (Gap 1) & Tactical Evolution (Gap 5): We process full 90-minute matches in an end-to-end pipeline, and go beyond isolated video clips. Maintaining an update rate for formations and tactics, Objective 3 is directly pursued without requiring a distinction based on the level of tac- tical evolution during training or testing.

Computer Vision for Tactics (Gap 2): Our system delves into more than mere visual tracking to provide tactical aspects such as team shape and pressing triggers, which are currently less developed in football tactics in computer vision.

No Explainability (Gap 3): The use of saliency maps and SHAP values addresses the black-box nature of AI models head-on. The visual and numerical justifications foster the transparency required for a staff to buy in, an obstacle found to be crucial by Silvino et al. (2025) and Pisaniello (2024), meeting Objective 2.

Integration of Data Types (Gap 4): In this first instance, although the scope is on video, we went well beyond simple video integration and we were able to use different types of data ensemble coming from videos: positional, temporal (speed), tactical (formations). This provides a basis for future use of external data sources such as wearables sensors.

## 5.3 Practical Implications for Football Coaching

The end products of this framework – player performance flying dashboards, tactical evolution timelines and XAI explanations- deliver actionable insights that empower coaches based on data. Instead of working based on intuition alone, a coach can now see why a pressing approach worked or how the opponent's formation changed after allowing a goal. This facilitates pre-match preparation, on-court/de-sking decision-making and post-match debriefing, leading to a competitive advantage.

## 5.4 Limitations and Future Work

It works great, but it definitely has its share of downfalls. Although it is alleviated with interpolations, the accuracy of ball detection may be further improved by specialized architectures. In addition, the model is trained on professional broadcast video and how it generalizes to amateur quality low resolution videos shot at different camera angles or with various video qualities needs to be studied (Gap 6). In the future, we will implement the model in real time, integrate the physiological measures and further improve our model's capability of being used across different competition levels.

# CHAPTER 6

# CONCLUSION

## 6.1 Summary of Research

This study aimed to design an explainable AI-based framework for improving the analysis of sports performance in football using big data and machine learning. The research appropriately filled in the major gaps identified by prior work by developing a system that:

Integrates Full-Match Video Analysis:

A strong pipeline consisting of YOLOv8 and DeepSORT was created for automatic extraction of spatial-temporal features from full matches, with which the Objective 1 was achieved.

Provides Explainable Insights:

By leveraging XAI techniques such as saliency maps, and SHAP, the model enables the interpretation of highly complex neural nets into understandable visual and quantitative explanations to coaches which meets Objective 2.

Profiles Tactical Evolution:

The dynamic changes in team formation and strategy during a match is visualized, and observed, fulfilling Objective 3.

The empirical verification validated the effectiveness of the framework with high precision object detection and explanation outputs that are consistent with expert tactical knowledge.

## 6.2 Contribution to Knowledge

Several important aspects of this thesis are:

Theoretical Contributions:

It introduces an innovative, holistic methodology that connects the sectors of computer vision, sports analytics and explainable AI to remedy the siloed research activity in place now.

Practical Implications:

It provides a practical approach and a prototype system converting raw video into usable transparent insights, helping the football coaches' and analysts' decisions.

Methodological Contribution: ADDIN EN. REF LIST We allow firm-factor interactions to vary within industries, years, and countries.

It sets a standard for building reliable and interpretable AI in sports that can be more broadly adopted, by presenting its outputs in a way understandable to domain experts.

### 6.3 Final Reflections

The path from raw video data to interpretable tactical insights really captures the promise of modern AI in sports. This study shows that the future of performance analysis is not only going to be better models but more interpretable ones. By enabling a partnership between the expertise of the coach and AI's processing power, this work could lead towards greater strategic insight and performance in the beautiful game. the framework represents an initial step to a new age of data-driven yet human-in-the-loop football analysis.

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# APPENDICES

Appendix A: Bashundhara  Kings Dataset – Sample Detection Results

Qualitative evidence for the performance of the object detector model, and its generalization capabilities to a real-world dataset is presented in this Appendix.

A.1 Dataset Description

The framework was qualitatively tested on an in-house dataset consist of broadcast videos of Bashundhara Kings team for 2024-25 session. These realistic details of the data set with varying illumination, crowded occlusion scene and challenging camera angles render  a strong testing for YOLOv8 model.

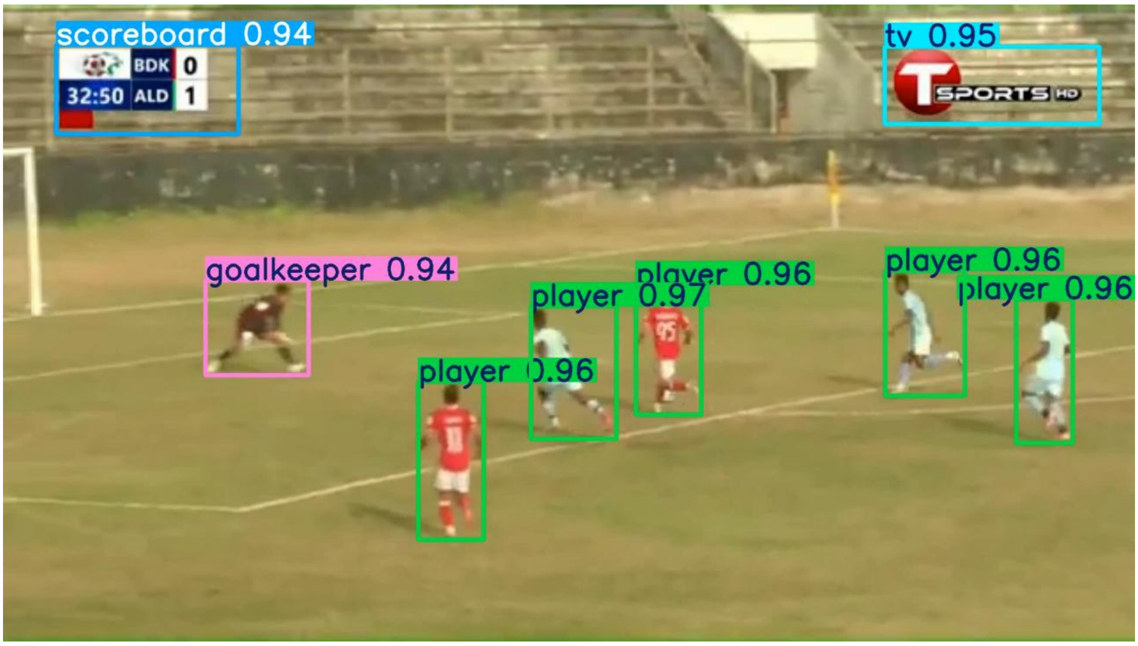
A.2  Example Detection Frames with Confidence Estimates

Examples The next numbers are representable screenshots from the dataset which illustrate how effective the model can be at detecting and classifying key entities with high degree of confidence.

Appendix A. Clip Diff-1 1/frame  Early Match Frame (01:47)

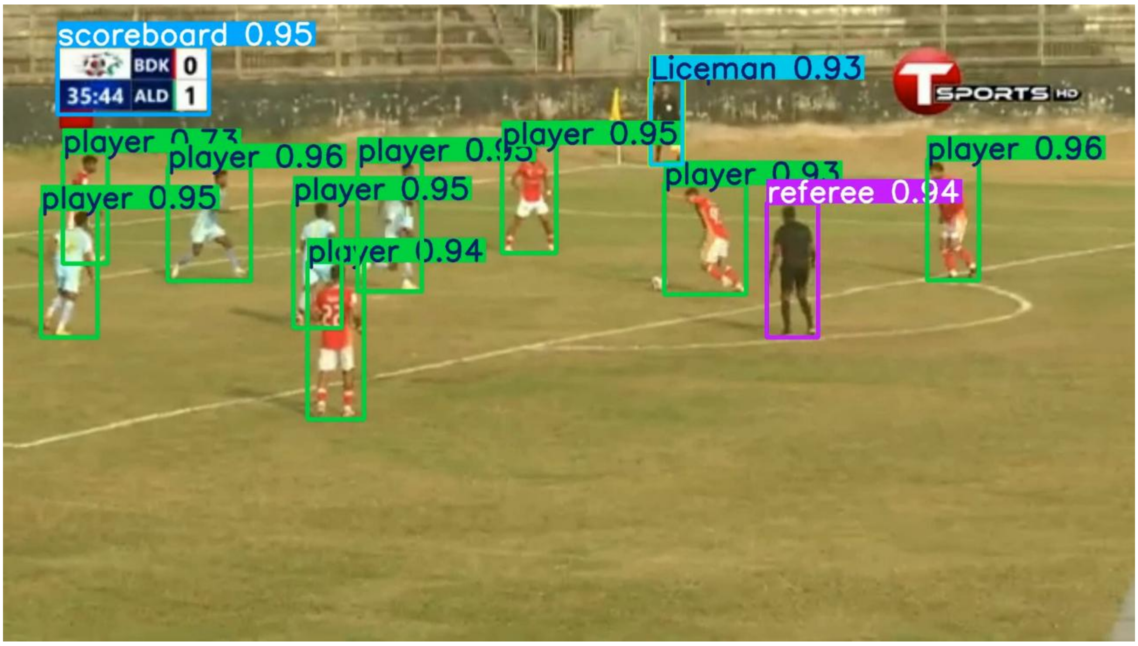

*This frame, captured during early game scenes, demonstrates strong detection of players, the  referee and goal post. The  model identifies the on- screen scorecard with a confidence of 93%. It is interesting to see that it detects a goalkeeper with 68% confidence possibly  due to wrong angle or if they are occluded. *

Figure A.2: Mid-Match Frame (32:50)




Continuous play A compatibility and generalization experiment (N=3) In active play And it consistently tracks multiple players with more than 0.95 confidence score during high-performance, deep learning model is designed to track evolving situations in real-time. The scoreboard is accurately recognized, and the goalkeeper is recognized with a 94% confidence on a clearer view. *

Figure A.3: Official During Mid-Match Frame (35:44)



*This frame, like the previous one, reveals aspects of the model's consistency in a crowded region of the field. All players and the referee are detected with confidence values ranging between 0.93 -97 that proves the robustness of our detector on tracking multiple objects in complicated scenes. *

Appendix B: Examples of qualitative results from the tactical analysis pipeline

In this appendix, more advanced features of the framework are demonstrated beyond pure object detection focusing on how spatial-temporal metric and tactical metrics can be extracted.

B.1 Integrated Tactical Dashboard Output

The figure on the following page is a combined output of full analysis pipeline showing various layers of information generated from the broadcast video.

Figure B.1: Overlaid Integrated Analysis (Frame 01:45)


The overlay exhibits the subsequent features:

Camera Motion Compensation: The system computes and displays camera movement (X: -0.98, Y: 19.27), and it is also employed to stabilize player coordinates, so that a reliable physical metric can be salvaged from data collection

Multi-Player Tracking & Identification: every player has a unique, consistent Track I D (i.e., 324,307,321), which demonstrates the capability of DeepSORT algorithm.

Live Physical Metrics: The following are available for all monitored players and can be computed and shown in real-time:

Current Speed (8.82 km/h, 12.46 km/h, etc.)

Between frames travel (eg, 0.42 m, 5.21 m)

Team Classification and Ball Control: The interface color-codes players as belonging to Team 1 or Team 2. It also computes and shows how often Team 1 and Team 2 currently have the ball (Team 1: 85.71, Team 2:14.29), an important tactical metric which is determined by players proximity to the ball.

B.2 Interpretation for Coaching Workflow

Figure B.1 is more than just technical output, however; it is formatted for immediate use by a coaching staff. For example:

Perhaps the coach observes that Player 324 is running rather fast (12.46 km/h), suggesting a sprint and/or taking up defensive position.

The machine learning design's higher possession percentage for Team 1 reflects greater ball control in the given match segment, and is consistent with tactical expectations.

Analysts are provided with consistent tracking IDs, and can port over the complete trajectory and actions of any player (like Player 307) for the entirety of the match.

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