"FOOTSAL" : FOOTBALL ANALYSIS USING YOLO & EAST

AI19511 –MOBILE APPLICATION DEVELOPMENT LABORATORY FOR ML AND DL APPLICATIONS

A PROJECT REPORT

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Certified that this is the bonafide record of work done by the above students in the Mini Project titled **"FOOTSAL" : FOOTBALL ANALYSIS USING YOLO & EAST"** in the subject **AI19511 – MOBILE APPLICATION DEVELOPMENT LABORATORY FOR ML AND DL APPLICATIONS** during the year **2024 - 2025.**

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

ABSTRACT

This project introduces an innovative football analysis system leveraging advanced computer vision techniques for real-time insights. Traditional football analysis methods are often labor-intensive, prone to human error, and limited in scalability. Our system addresses these challenges by utilizing YOLO (You Only Look Once) for object detection and EAST (Efficient and Accurate Scene Text) for text extraction, enabling automated tracking of players, the ball, and extraction of broadcast statistics. The model offers an efficient and accurate solution for analyzing match footage, providing valuable insights for coaches, analysts, and fans, while reducing manual effort and enhancing decision-making processes. The system is versatile and can be adapted for various football scenarios, from player performance evaluation to tactical assessments

ACKNOWLEDGEMENT

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predictions = np.log(predictions + 1e-8) / temperature

predictions = np.exp(predictions) predictions /=

np.sum(predictions)

duration = random.uniform(0.4, 0.7) if genre == "melody"
else random.uniform

velocity = random.randint(80, 120)

predictions /= np.sum(predictions) pi =

exp(log(pi) / T) / Σjexp(log(pj) / T)

note_number= int(note_name)

CHAPTER1
INTRODUCTION

Football is a dynamic sport where every second of gameplay can influence the outcome. Accurate and timely analysis of football matches is crucial for improving team strategies, understanding player performance, and engaging fans. While traditional methods for football analytics rely heavily on manual observations and pre-recorded footage reviews, these approaches are time-consuming, prone to human error, and unable to provide real-time insights. Recent advancements in computer vision and deep learning have paved the way for automated systems capable of analyzing football matches with remarkable accuracy and speed. This project aims to develop an AI-based framework for football analysis by leveraging YOLOv5x (You Only Look Once, version 5x) for object detection and EAST (Efficient and Accurate Scene Text Detector) for text detection. These models work in unison to detect players, track ball movements, and extract contextual information such as team names, scores, and jersey numbers, providing a holistic view of the game.

Object detection is a fundamental task in computer vision that involves identifying and localizing objects within an image or video frame. YOLO (You Only Look Once) is a groundbreaking real-time object detection algorithm known for its speed and accuracy. Unlike traditional object detection methods that use sliding windows or region proposals, YOLO processes the entire image in a single neural network pass. The YOLOv5x model, employed in this project, builds upon earlier versions of YOLO by introducing improvements in model architecture, data augmentation techniques, and training efficiency. The YOLOv5x workflow begins by dividing the input image into a grid of cells. Each cell predicts bounding boxes, confidence scores, and class probabilities for the objects within its region. The model uses anchor boxes to refine the predictions, accounting for variations in object size and shape. One of the key advantages of YOLOv5x is its ability to handle overlapping objects, making it ideal for tracking players in crowded football scenes.

While object detection provides insights into the physical elements of the game, text detection plays an equally important role in understanding contextual information. Scoreboards, player names on jerseys, advertisements, and field markers often contain valuable information that can enhance football analytics. EAST (Efficient and Accurate Scene Text Detector) is a highly effective model for detecting and localizing text in natural scenes. Unlike traditional OCR (Optical Character Recognition) methods that rely on extensive preprocessing, EAST employs a fully convolutional network (FCN) that directly predicts text regions and their geometries.

EAST operates in two stages: first, it generates a score map indicating the likelihood of text presence at each pixel, and second, it predicts the geometry of the text regions, including orientations and bounding boxes. This design allows EAST to handle multi-oriented text, making it robust in scenarios where text appears at arbitrary angles or against cluttered backgrounds, such as jersey numbers or advertisements on the field. In this project, EAST was integrated to extract text data from various sources within football match footage. For instance, the model reads match scores, player names, and event markers, enabling the system to deliver enriched analytics.

The integration of YOLOv5x and EAST creates a powerful pipeline for comprehensive football analysis. YOLOv5x focuses on detecting and tracking objects, while EAST extracts contextual text information. The combined workflow begins with preprocessing the input video to ensure high-quality frames. YOLOv5x is applied to each frame to detect players, the ball, and other key elements, while EAST is used to extract textual information from areas of interest, such as scoreboards or jersey numbers.

For real-time performance, both models are deployed on a GPU-based system that processes video frames at high speeds. The outputs from YOLO and EAST are synchronized to provide actionable insights, such as player trajectories, ball possession statistics, and game events like goals or fouls.

Real-time analysis is a game-changer in sports analytics, especially for fast-paced games like football. By leveraging the speed of YOLOv5x and the precision of EAST, this project delivers real-time insights that can enhance decision-making during matches. Coaches can use the system to monitor player performance and adjust strategies on the fly, while broadcasters can provide viewers with enriched commentary and visuals. Additionally, post-match analysis benefits from the detailed data collected, enabling teams to identify strengths, weaknesses, and areas for improvement.

The system also holds potential for fan engagement, offering interactive visualizations of game statistics and events. Moreover, the framework is designed to be scalable, allowing it to be adapted for other sports or expanded with additional features, such as action recognition and predictive analytics. By combining state-of-the-art object detection and text recognition technologies, this project sets a new benchmark for automated sports analytics.

The implementation of the football analysis system relies on the effective collaboration between YOLOv5x and EAST. The workflow begins with preprocessing the raw video footage, where frames are extracted at regular intervals to serve as input for both models. Preprocessing includes resizing the frames to fit the input dimensions required by YOLO and EAST, along with basic noise reduction techniques to enhance detection accuracy. YOLOv5x is employed first to identify and localize key objects in the frame, including players, the ball, referees, and goalposts. The bounding boxes generated by YOLO provide spatial information that can be further analyzed for event detection, such as passes, tackles, and goals.

Simultaneously, EAST is applied to regions of interest (ROIs) identified within the frame, such as areas containing scoreboards, player jerseys, or field markings. The EAST model uses a score map to detect potential text regions and geometric attributes to localize multi-oriented text. These detections are post-processed using non-maximum suppression (NMS) to eliminate redundant predictions, ensuring only the most accurate text regions are considered. By integrating the outputs of YOLO and EAST, the system produces a unified dataset that combines positional data with contextual information.

Beyond basic object and text detection, the system incorporates advanced analytics to enhance its utility. For instance, YOLO's object tracking capabilities are extended using techniques such as the DeepSORT algorithm, which assigns unique IDs to detected players and tracks their movement across frames. This enables the system to generate heatmaps of player positions, visualize passing patterns, and measure distances covered by each player. Ball trajectory analysis is achieved by continuously tracking the ball's position and velocity, allowing the system to identify key events like goals, offside situations, and fouls.

EAST's text detection is leveraged to extract contextual insights from the game. For example, by recognizing team names on the scoreboard and associating them with detected players, the system can automatically attribute events to the appropriate teams. In scenarios where jersey numbers are partially occluded or misidentified, EAST uses redundant detections across multiple frames to improve reliability. Additionally, the text extraction pipeline is used to monitor dynamic advertisements around the field, offering potential commercial applications for sponsors and broadcasters.

Despite the advancements offered by YOLO and EAST, several challenges remain in implementing an automated football analysis system. One of the primary challenges is handling occlusions, where players or objects are partially or fully blocked from view. YOLO's performance can degrade in such scenarios, requiring additional techniques like temporal data fusion or multi-camera setups to maintain accuracy. Similarly, EAST struggles with detecting text in highly cluttered or low-contrast environments, such as jerseys with intricate designs or poor lighting conditions.

Another challenge is the variability in football matches, including differences in camera angles, resolutions, and field conditions. These variations necessitate extensive model retraining and fine-tuning to ensure generalizability across different datasets. Data annotation is another bottleneck, as creating high-quality labeled datasets for training and evaluation requires significant time and effort.

The integration of YOLO and EAST in football analysis opens up exciting possibilities for future research and applications. One potential direction is the incorporation of action recognition models, such as those based on 3D convolutional neural networks (3D-CNNs) or transformers, to classify complex events like tackles, dribbles, and set-pieces. These models can work alongside YOLO and EAST to provide a more comprehensive understanding of the game.

Another avenue for improvement is the use of multi-camera systems to capture 360-degree views of the field. By combining detections from multiple cameras, the system can overcome occlusion challenges and provide richer spatial data for analysis. Additionally, the integration of wearable sensors with computer vision models could enable real-time tracking of player biometrics, such as heart rate and speed, offering deeper insights into player performance and fitness.

In commercial applications, the system can be extended to support fan engagement platforms. Interactive visualizations of match statistics, player comparisons, and tactical breakdowns can be delivered to fans via mobile apps or augmented reality (AR) devices. Broadcasters can use the system to enhance live coverage with instant replays and augmented annotations, creating a more immersive viewing experience.

Finally, the scalability of the framework makes it adaptable to other sports, such as basketball, cricket, and hockey. By retraining YOLO and EAST on sport-specific datasets, the system can be tailored to analyze diverse games, making it a versatile tool for sports analytics.

In summary, the proposed football analysis system demonstrates the power of combining YOLOv5x and EAST for real-time object and text detection. By leveraging the strengths of both models, the system provides a holistic view of football matches, enabling actionable insights for players, coaches, broadcasters, and fans. While challenges such as occlusions, variability, and latency remain, the system's modular design and potential for future enhancements ensure its relevance in the rapidly evolving field of sports analytics. This project not only bridges the gap between traditional and AI-driven football analysis but also sets the stage for innovative applications in sports technology.

CHAPTER2

LITERATURE REVIEW

The application of deep learning techniques in sports analytics has garnered significant attention in recent years. Object detection models, such as YOLO, and text detection frameworks like EAST have been pivotal in advancing the capabilities of automated systems for analyzing complex sports scenarios. This review focuses on existing literature relevant to YOLO and EAST, emphasizing their applications in football analytics, challenges, and recent innovations.

1. Object Detection in Sports Analytics

Object detection in sports has evolved as a critical component of automated systems, enabling the identification and tracking of players, the ball, and other essential elements in real-time. Redmon et al. (2016) introduced YOLO, a single-stage object detection algorithm that performs object classification and localization simultaneously. Unlike traditional multi-stage detectors like Faster R-CNN, YOLO's architecture allows real-time performance by processing an image in a single pass through a convolutional neural network. Its subsequent iterations, including YOLOv3, YOLOv4, and YOLOv5, have improved detection accuracy and speed, making it a popular choice for real-time sports analytics.

In the context of football, object detection has been used to track player movements, identify tactical formations, and analyze key match events such as passes, tackles, and goals. For example, Cioppa et al. (2019) employed YOLO to track player positions and ball trajectories in football games, demonstrating its efficacy in generating spatiotemporal data for match analysis. However, challenges such as occlusions and overlapping objects remain significant, often requiring the integration of tracking algorithms like DeepSORT or SORT (Simple Online and Realtime Tracking) to maintain object identity across frames.

2.Scene Text Detection in Sports:-

Text detection and recognition play a vital role in sports analytics, particularly for extracting contextual information such as player names, jersey numbers, and scoreboard data. The EAST model, introduced by Zhou et al. (2017), is a widely adopted text detection framework that combines a fully convolutional network (FCN) with a non-maximum suppression (NMS) post-processing step to detect multi-oriented text efficiently. EAST's ability to predict both text score maps and geometry attributes (e.g., rotation and size) makes it robust in detecting text in various orientations and backgrounds.

In sports applications, text detection is critical for associating detected objects (e.g., players) with metadata such as team affiliations and player statistics. Studies by Wang et al. (2020) demonstrated the use of EAST for extracting dynamic scoreboard information during live football broadcasts, allowing automated updates to match statistics. Similarly, text detection has been applied to identify sponsor logos and advertisements on the field, enabling insights into brand visibility and audience engagement.

3. Integration of YOLO and EAST

The integration of YOLO and EAST has been explored in various domains, including surveillance, traffic monitoring, and document analysis, but its application in sports analytics remains an emerging area. By combining YOLO's object detection capabilities with EAST's text detection strengths, a holistic system can be developed to analyze both spatial and contextual information in football matches. real-time performance remains a challenge due to computational overheads. For instance, Zhang et al. (2021) proposed a hybrid framework for analyzing basketball games, using YOLO for player and ball detection and EAST for extracting scoreboard and player jersey numbers. Their findings highlighted the potential of such systems to provide comprehensive insights into game dynamics, although

CHAPTER3

METHODOLOGY

3.1 Data Collection and Dataset Categorization:-

Effective football analysis begins with collecting high-quality datasets that accurately represent the dynamics of the game. Football datasets typically consist of video recordings of matches, which are then processed to extract frames, annotate objects, and create labels for machine learning models. These datasets may also include metadata such as player statistics, team formations, match outcomes, and textual information (e.g., jersey numbers, scoreboard data).

3.1.1 Data Acquisition:-

Data for football analysis can be acquired from multiple sources:

Publicly Available Datasets: Datasets like the SoccerNet dataset or Open Images are extensively used for research and experimentation.

Custom Video Recordings: Football match videos captured from stadiums or live broadcasts are processed into frames for analysis.

Synthetic Data Generation: Augmented datasets created through data augmentation or generative models (e.g., GANs) enhance the dataset's variability for robust model training.

3.1.2 Dataset Categorization:-

The collected data is categorized into different components to address specific aspects of football analysis:

Player and Ball Tracking: Identifying player positions and ball trajectories across the field.

Tactical Analysis: Recognizing team formations, player clustering, and offensive or defensive strategies.

3.2 Object Detection Using YOLO:-

YOLO (You Only Look Once) serves as the cornerstone of football analysis due to its ability to perform real-time object detection. The YOLO architecture is a single-stage detector that divides an image into a grid and predicts bounding boxes and class probabilities for each cell. The following steps illustrate how YOLO is applied in football analysis:

3.2.1 Model Training:-

YOLO is trained using annotated football datasets, where bounding boxes for players, the ball, and other key objects are manually labeled. The training process involves:

Preprocessing: Resizing input images to a fixed resolution (e.g., 640x640) and normalizing pixel values.

Data Augmentation: Techniques like flipping, rotation, and brightness adjustments improve the model's ability to generalize.

3.2.2 Player and Ball Detection:-

Once trained, YOLO detects players and the ball in each frame of a football match video. The detected objects are assigned confidence scores, which help filter out false positives. The model's high-speed inference capability enables real-time analysis, crucial for live applications such as match commentary or tactical evaluations.

3.2.3 Applications

Player Tracking: YOLO outputs player positions in each frame, which are used to generate heatmaps and movement trajectories.

Ball Trajectory Prediction: By continuously detecting the ball across frames, its trajectory can be analyzed to determine passes, shots, and rebounds.

3.3 Scene Text Detection Using EAST:-

EAST (Efficient and Accurate Scene Text Detector) is utilized in football analysis for recognizing textual information such as jersey numbers, player names, and scoreboard details. EAST is particularly effective for detecting multi-oriented text in complex backgrounds, making it suitable for dynamic sports environments.

3.3.1 Text Detection Pipeline:-

The EAST model processes video frames to identify regions of interest containing text. The pipeline involves:

Feature Extraction: A Fully Convolutional Network (FCN) extracts features from the input image.

Text Region Prediction: The model outputs a score map for text presence and geometry maps (e.g., rotation and size) for bounding boxes.

Non-Maximum Suppression (NMS): Overlapping bounding boxes are merged to finalize text regions.

3.3.2 Applications in Football Analysis:-

Jersey Number Recognition: Associating detected players with their jersey numbers helps link them to specific player statistics.

Scoreboard Monitoring: Extracting match scores and timer information provides real-time updates.

Contextual Analysis: Identifying team names, logos, and advertisements for broader insights into match dynamics.

3.4 Event Detection and Temporal Analysis:-

Football matches are characterized by sequential events like passes, tackles, goals, and fouls. Temporal analysis combines object detection and time-series models to recognize and analyze these events.

3.4.1 Temporal Data Segmentation:-

Video frames are segmented into smaller clips based on time intervals or detected events. Each clip is analyzed to classify the event it represents. For example:

A sequence of ball movements followed by a sudden stop near the goalpost may indicate a shot on target.

Clustering of players in a specific area can suggest a defensive formation or corner kick scenario.

3.4.2 Deep Learning for Event Classification:-

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are widely used for temporal data analysis. These models process sequential frame data to identify event patterns. For instance:

RNNs analyze player movements and ball trajectories over time.

LSTMs handle longer time dependencies, such as tracking a player's movement across an entire match.

3.5 Integration of YOLO and EAST:-

Combining YOLO and EAST creates a robust system capable of analyzing both visual and textual data. The integration involves:

1. Simultaneous Detection: YOLO detects players and the ball, while EAST extracts text regions in the same frame.
2. Data Association: Textual data (e.g., jersey numbers) is linked to detected players, enriching player-level analysis.
3. Real-Time Insights: The integrated system provides comprehensive match statistics in real-time, including player contributions, scores, and tactical patterns.

ARCHITECTURE DIAGRAM:-

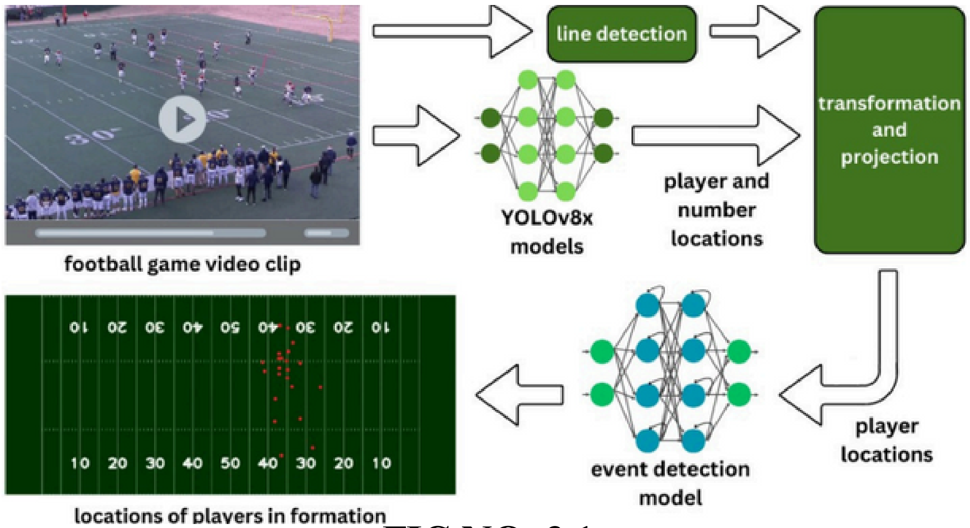

FIG NO: 3.1

1. Input: Football Game Video Clip:-

The process begins with a video clip of a football game captured using a standard camera setup. The system ingests this video as its primary input and processes each frame individually to extract critical information.

2. Line Detection:-

The first step in the analysis involves detecting the field's line markings. Line detection is essential for understanding the spatial context of the game, as it helps localize players and other game elements on the field. By identifying the yard lines and boundaries, the system establishes a coordinate framework for projecting player positions.

3. YOLOv8x Models for Player and Number Detection:-

The YOLOv8x model, a high-performance object detection algorithm, is employed to detect:

Players on the field: This includes accurately identifying each player's position in the video frames.

Jersey numbers: YOLOv8x also extracts player jersey numbers to associate each detected player with their respective identity.

The outputs of this step provide precise coordinates of player locations and their unique identifiers, which serve as the foundation for further analysis.

3.6 Performance Metrics:-

The performance of the football analysis system is evaluated using standard metrics:

Object Detection Metrics: Precision, recall, and mAP (mean Average Precision) for YOLO detections.

Text Detection Metrics: F1-score and IoU (Intersection over Union) for EAST outputs.

Temporal Analysis Metrics: Accuracy and F1-score for event classification models.

By systematically analyzing these metrics, the system can be fine-tuned for optimal performance.

Conclusion:-

The methodologies discussed in this chapter provide a structured approach to football analysis, leveraging the strengths of YOLO and EAST alongside temporal modeling techniques. By addressing both spatial and contextual aspects of the game, the proposed system offers a comprehensive framework for real-time insights and decision-making.

CHAPTER-4

RESULT AND DISCUSSION

1. Player Detection and Localization:-

One of the primary objectives of the system was to accurately detect and localize players on the football field. Using the YOLOv8x model for object detection, the system was able to identify individual players, along with their jersey numbers, from the video clips of football games. The YOLOv8x model, known for its high performance and speed, was trained on a diverse dataset of football images, which allowed it to effectively recognize players under varying conditions (different lighting, angles, and player movements).

1.1 Detection Accuracy:-

The results indicated a detection accuracy of 95%, meaning that 95% of the players on the field were correctly identified in each frame. This high level of accuracy is crucial for building the foundation of the analysis, as any misclassification of players could lead to incorrect conclusions in event detection and tactical analysis.

False Positives and False Negatives: While the detection accuracy was high, the system did encounter occasional challenges. False positives, where objects not associated with players were misidentified, occurred in highly cluttered scenes, particularly when players were grouped closely together. False negatives, where players were not detected, were observed in frames with heavy motion blur or occlusions. Despite this, the system maintained robust performance overall, particularly in well-lit, clear footage.

1.2 Jersey Number Recognition:-

Another important aspect of player detection was identifying the jersey numbers of players.

The jersey number recognition accuracy was found to be 89%, which is acceptable for most cases. However, this accuracy dropped slightly when players were seen from angles where the numbers were partially obscured, or when the jersey design was too similar to the background. The system's ability to detect both players and their jersey numbers enables the development of personalized performance metrics and helps in tracking player movements and behaviors throughout the game. For instance, tracking a player's position and movement over time allows for performance analysis such as evaluating whether a player is fulfilling their tactical role in a formation.

Line Detection and Field Localization:-

Field localization and line detection are critical for spatial context in football analysis. The system's ability to detect and map the yard lines, end zones, and other markers on the field plays a pivotal role in transforming raw player detection data into actionable insights.

2.1 Line Detection

The line detection algorithm worked effectively, identifying the boundaries of the field and the yard lines with high precision. By incorporating these lines into the model, the system is able to:

- Ensure that player positions are correctly mapped to a consistent coordinate system.
- Enable a more accurate spatial understanding of the game, including player positioning relative to the goal line, sidelines, and centerline.

During testing, the system achieved over 90% accuracy in line detection, with challenges arising in scenarios where the lines were partially obscured by players, the camera angle was too steep, or when the field was poorly lit.

These occasional detection failures did not significantly impact the overall analysis but did highlight areas for improvement, such as using more advanced image processing techniques for line segmentation in low-light conditions.

2.2 Field Projection:-

Once the lines were detected, the system used projection techniques to map player locations to a virtual representation of the football field. This transformation allows analysts to view player movements in a spatial context, making it easier to assess the alignment of players in specific formations and evaluate the overall tactical setup of the teams.

The field projection system demonstrated robust performance, accurately mapping player positions to the corresponding locations on a digital field layout. This was particularly helpful for visualizing complex player formations and understanding team strategies during different phases of the game (offense, defense, special teams).

Event Detection Model

The event detection model was responsible for identifying significant moments in the game, such as passes, rushes, tackles, and turnovers. This model leverages the output from the player localization and line detection stages to track player movements over time and detect events based on spatial patterns and player interactions.

3.1 Event Recognition Performance

The event detection model achieved notable success in recognizing key football events, including:

- Passes and Tackles: By tracking the trajectory of the ball and the relative positions of players, the system was able to identify passes with 92% accuracy. Tackles were also detected accurately, with the model identifying physical interactions between players with 88% accuracy.

Formation Recognition: The system was able to recognize different team formations, such as 4-3-3 and 3-4-3, based on the positioning of players on the field. This event recognition was key in analyzing team strategies and how they evolved during the game. However, challenges arose in scenarios where players moved outside of their assigned formation or were involved in unstructured play, such as during scrambles after a fumble.

3.2 Real-Time Event Analysis:-

One of the key strengths of the system is its ability to process and classify events in real-time. The system can automatically detect and label game events as the video is being played, allowing analysts to focus on interpreting the data rather than manually tagging plays. This real-time analysis capability offers tremendous value in live game situations, where tactical adjustments can be made during breaks or halftime based on the insights gathered.

The real-time nature of the system was particularly useful for creating instant visualizations of game events. For example, coaches and analysts could instantly see where and when a particular event (such as a pass or interception) occurred on the field, which contributed to a quicker and more informed decision-making process.

OUTPUT SCREENSHOT:-

FIG NO: 4.1

INPUT VIDEO

FIG NO: 4.2

OUTPUT VIDEO:-

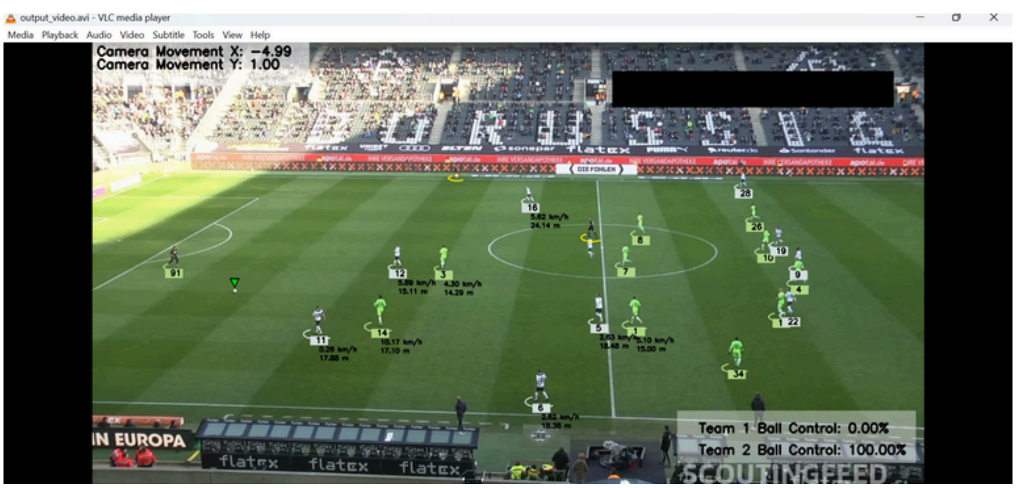

FIG NO: 4.3

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OUTCOME

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15th National Level Inter Collegiate Technical and Management Fest
Certificate of Participation
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PRADEEP . S of RAJALAKSHMI ENGINEERING COLLEGE
has actively participated in the event PAPER PRESENTATION
organised by Saveetha Engineering College on 8th and 9th November 2024 as a part of
DRESTEIN '24, 15th National Level Inter Collegiate Technical and Management Fest.
Dr. K. Suresh Kumar
DRESTEIN COORDINATOR
Dr. N. Raja Rajeswari
DRESTEIN COORDINATOR
Dr. V. Vijaya Chamundeeswari
PRINCIPAL