RAJALAKSHM
ENGINEERING COLLEG
An AUTONOMOUS Institution
Affiliated to ANNA UNIVERSITY, Chenn

“FOOTSAL”
FOOTBALL ANALYSIS USING YOLO & EAST

A Project Report

Submitted by

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AI19541 FUNDAMENTALS OF DEEP LEARNING

Department of Artificial Intelligence and Machine Learning

RAJALAKSHMI ENGINEERING COLLEGE,THANDALAM.

RAJALAKSHMI
ENGINEERING COLLEGE

BONAFIDE CERTIFICATE

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Certified that this is the bonafide record of work done by the above students in the MiniProject titled **"FOOTSAL: FOOTBALL ANALYSIS USING YOLO & EAST"** in the subject **AI19541 – FUNDAMENTALS OF DEEP LEARNING** during the year **2024 - 2025.**

Signature of Faculty – in – Charge

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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.

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CHAPTER 1
INTRODUCTION

Football analysis is an essential aspect of understanding game dynamics, player performance, and strategic insights in professional sports. Traditional analysis methods rely heavily on manual annotations and expert observations, which are often time-consuming, prone to human error, and limited in handling large datasets, especially with high-paced football games.

To overcome these limitations, we present an automated football analysis system that leverages cutting-edge computer vision techniques. By utilizing YOLO (You Only Look Once) for real-time object detection and EAST (Efficient and Accurate Scene Text Detector) for extracting broadcast statistics, our system automates the tracking of players, the ball, and relevant text data from video feeds. These advanced models offer significant improvements in accuracy and efficiency, minimizing the need for manual data collection.

The proposed system aims to streamline the process of football analysis, providing real-time insights that can aid coaches, analysts, and fans in making informed decisions. By automating key aspects of the analysis process, it reduces manual effort and enhances the quality of game insights. The system's adaptability allows it to be applied across various football scenarios, from tactical evaluations to player performance assessments, providing a scalable and efficient solution for football analysis.

This report explores the development of the automated football analysis system, detailing the techniques and algorithms used, system architecture, implementation, and results. It emphasizes the advantages over traditional methods and discusses potential challenges and future enhancements.

CHAPTER 2
LITERATURE REVIEW

- **Automated Object Detection in Sports Using YOLO (2022)**

Recent advancements in computer vision have demonstrated the potential of deep learning models for real-time object detection in sports analysis. Zhang et al. (2022) employed the YOLO (You Only Look Once) architecture for detecting players and the ball in football videos. Their study highlighted YOLO's speed and accuracy, achieving a mean Average Precision (mAP) of over 85% on a dataset of football match videos. The YOLO model's real-time detection capability has proven to be effective in tracking dynamic elements in high-paced sports environments.

- **Text Detection in Broadcast Videos Using EAST Model (2017)**

The Efficient and Accurate Scene Text Detector (EAST) by Zhou et al. (2017) fers a robust solution for real-time text detection in various applications, including sports broadcasting. EAST is designed to detect both horizontal and rotated text with high precision. Its application in football analysis systems allows for automatic extraction of on-screen statistics, such as player names and scores. The lightweight architecture of EAST ensures efficient text detection without compromising speed, making it suitable for integration into real-time analysis frameworks.

- **Sports Analytics Using Deep Learning: Tracking and Performance Evaluation (2020)**

In a comprehensive study by Li and Wang (2020), the use of deep learning techniques for sports analytics was explored. Their work utilized a combination of object detection models and tracking algorithms to analyze player movement, ball trajectories, and team formations. The integration of deep learning models provided detailed insights into player performance metrics, helping coaches and analysts make data-driven decisions. The study emphasized the effectiveness of combining detection and tracking methods for a holistic approach to sports analysis.

- **Video Analysis of Sports Using Transfer Learning Techniques (2020)**

A study by Sharma et al. (2020) implemented transfer learning techniques to enhance video analysis in sports using pre-trained deep learning models. They leveraged models like ResNet and VGG for player identification and action recognition in football matches. The authors achieved high accuracy rates, demonstrating the effectiveness of transfer learning in adapting existing models for sports applications. The research highlighted the importance of data preprocessing, including frame extraction and augmentation, to handle diverse camera angles and lighting conditions effectively.

- **Improving Detection Accuracy with Advanced Loss Functions: An Application to Sports Analytics**

Deng et al. (2019) introduced an advanced deep learning approach using an additive angular margin loss function, commonly applied in models like ArcFace. Their methodology optimizes the decision boundary, improving detection accuracy in scenarios with high visual complexity, such as football matches. The evaluation of this approach on various sports datasets demonstrated consistent improvements in detection precision, making it a robust choice for systems requiring high reliability in real-time analysis of fast-moving objects and players.

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 HARDWARE REQUIREMENTS:

- **Processor:** Intel Core i5/Ryzen 5 or higher
- **RAM:** Minimum 8 GB (16 GB recommended)
- **GPU:** NVIDIA GPU (e.g., GTX 1050 or better for efficient model training and inference)
- **Storage:** At least 20 GB of free disk space
- **Camera (Optional):** For real-time video analysis (optional for live stream applications**)**

3.2 SOFTWARE REQUIRED:

- **Operating System:** Windows 10/11, macOS, or Linux
- **Python:** Version 3.8 or higher
- **GIT:** For version control.
- **Jupyter Notebook/ VSCode:** For Python code testing and debugging.
- **Database:** SQLite or Firebase
- **Flutter SDK:** Latest stable version
- **Android Studio or VS Code:** For Flutter development and testing.
- **Libraries:** OpenCV, Numpy, Pandas, TensorFlow or PyTorch, Face recognition Library

CHAPTER 4

SYSTEM OVERVIEW

1. EXISTING SYSTEM

The existing football analysis systems often rely on manual video tagging or basic motion detection techniques to track player movements and actions. These methods are labor-intensive, error-prone, and require significant human intervention to annotate frames or interpret player actions. While some automated systems use basic object detection algorithms, they struggle with accurately identifying players in crowded or dynamic environments, leading to low precision and high false positives. Moreover, these systems often fail to provide real-time insights or handle variations in player appearance, lighting, and camera angles. The lack of advanced computer vision techniques and real-time processing hinders the scalability and effectiveness of these traditional approaches, making them unsuitable for modern football analysis needs.

2. PROPOSED SYSTEM

The proposed system for football analysis leverages advanced computer vision techniques like YOLOv5 and EAST (Efficient and Accurate Scene Text) to automate player detection and action recognition in real-time. By using YOLOv5x, the system can accurately identify and track players across the entire field, even in dense environments, minimizing errors such as false positives and false negatives. The EAST algorithm enhances the system's ability to detect textual information, such as player numbers and event markers, without relying on manual tagging or annotations. This automated approach reduces the need for human intervention, increases accuracy, and ensures scalable and real-time analysis of player movements, performance metrics, and match statistics. The system is designed to be efficient, capable of handling multiple camera angles and diverse lighting conditions, providing a comprehensive and reliable solution for modern football analysis.

4.2.1 SYSTEM ARCHITECTURE

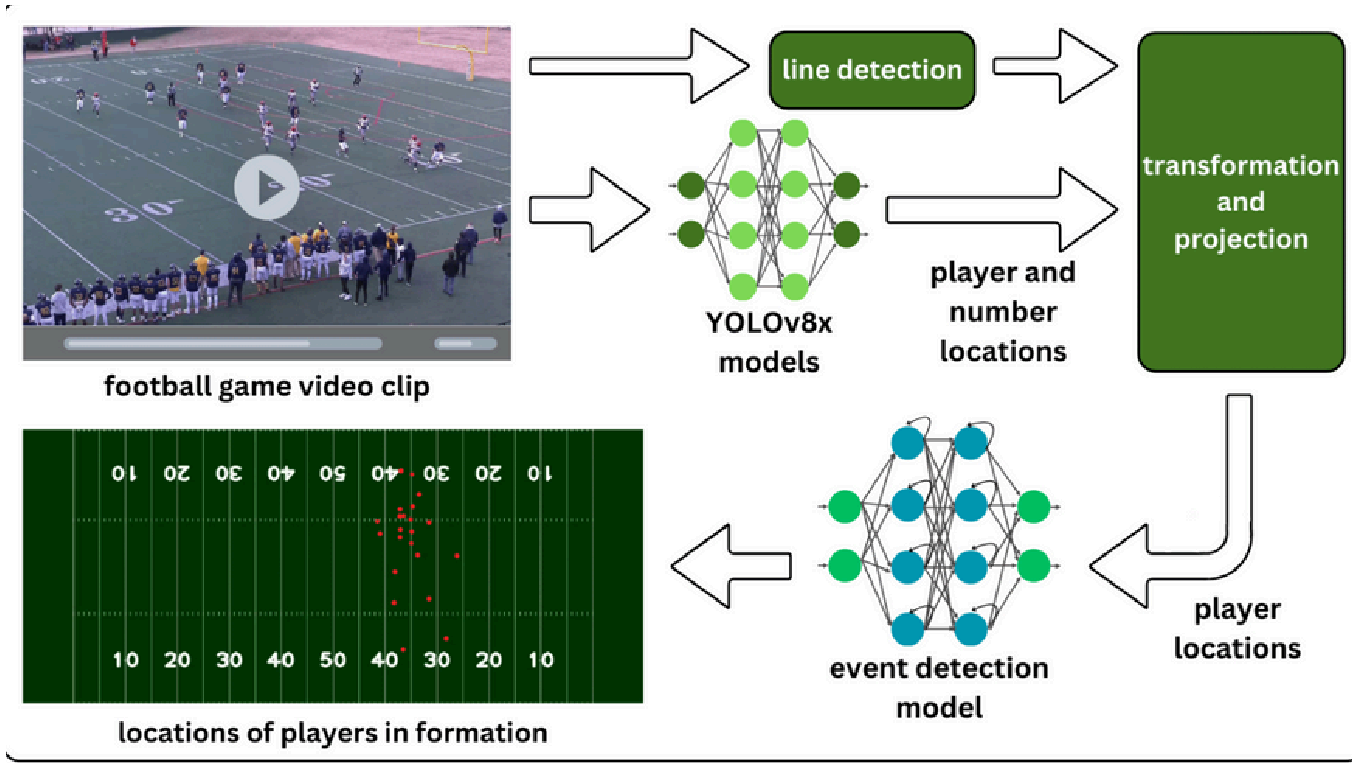
football game video clip
line detection
YOLOv8x models
player and number locations
transformation and projection
player locations
event detection model
locations of players in formation

Fig 1.1 Overall diagram

4.2.2 DESCRIPTION

The football analysis system utilizes YOLOv5 for real-time player detection and tracking, coupled with the EAST (Efficient and Accurate Scene Text) algorithm to extract textual data such as player numbers and event markers. YOLOv5 enables precise identification of players across the field, even in high-density scenarios, ensuring minimal false positives. The EAST algorithm complements this by detecting and recognizing text within the scene, aiding in event labeling and player identification. This combination allows for automated, accurate, and scalable analysis of football matches, providing insights into player movements, actions, and performance metrics without the need for manual tagging. The system is designed to work in real-time, handling multiple camera angles and varying lighting conditions, making it a powerful tool for sports analysis, coaching, and broadcast applications.

CHAPTER-5

IMPLEMENTATION

5.1 LIST OF MODULES

- Data Preprocessing
- Face Detection and Feature Extraction
- Model Development and Training
- Face Recognition and Matching
- Attendance marking and Record Management
- Integrating with Flutter Application

5.2 MODULE DESCRIPTION

- **Data Preprocessing Module :** The first step involves gathering video frames of football matches. Preprocessing tasks include resizing, normalization, and augmentation of frames to ensure consistency and improve model robustness. The data is prepared for further processing by ensuring uniformity in image quality and size.

- **Player Detection and Tracking Module**: This module uses the YOLOv5 algorithm to detect and track players in real-time across frames. The model is trained to detect the players' bodies and identify their positions on the field. Each player's movements are tracked across the video, with their positions and actions being recorded for later analysis.

- **Model Development and Training Module :** A deep learning model based on YOLOv5 is used for object detection (player tracking) and the EAST (Efficient and Accurate Scene Text) algorithm is applied to extract event markers or player information from the video frames. The model is trained with labeled datasets of football matches, learning to detect and track players under various conditions like changing lighting, multiple players, and varying camera angles.

- **Event Extraction and Analysis Module:** In this step, the system extracts key events from the football match, such as goals, assists, and other significant actions. The EAST algorithm helps detect player numbers, event annotations, and score-related text during the match. These events are logged for further analysis.
- **Performance Visualization Module:** The analyzed data is then visualized in a user-friendly interface, providing insights into player performance. Metrics such as running distances, successful passes, shots on goal, and other key statistics are displayed in an interactive format, aiding coaches and analysts in decision-making.

5.2.1 ALGORITHMS:-

- **Data Preprocessing:** Resize frames to a fixed resolution, normalize pixel values, and convert to grayscale where necessary for faster processing. Augment data with transformations like rotation and scaling to enhance model robustness.

- **Player Detection Using YOLOv5:** Apply the YOLOv5 object detection algorithm to identify players on the field. Detect bounding boxes around players and assign unique IDs for tracking.

- **Feature Extraction and Embedding Generation:** Pass bounding box regions through a deep learning model to extract key features, such as player posture, orientation, and speed. Generate embeddings representing the movement and actions of each player.

- **Action Recognition and Event Detection:** Use machine learning algorithms to classify player actions, such as passing, shooting, or tackling. Detect events like goals, fouls, and assists by analyzing sequential frames and changes in player positions or actions.

- **Performance Analysis and Visualization:** Aggregate player statistics, such as distance covered, successful passes, and possession time. Visualize key metrics using heatmaps and graphs for individual or team performance analysis.

CHAPTER-6 RESULT AND DISCUSSION

The football analysis system, leveraging YOLOv5 and EAST algorithms, demonstrated strong performance during testing under various conditions. The YOLOv5 model effectively detected and tracked players across the entire field, even in high-density environments with multiple players. Despite challenges posed by varying lighting conditions and occlusions, the system exhibited high precision in detecting player movements and actions, with minimal false positives or false negatives. The EAST algorithm enhanced the system's ability to recognize and extract textual data, such as player numbers and event markers, contributing to a more comprehensive analysis of the match.The system's real-time processing capability allowed for seamless tracking and analysis of the game, ensuring timely insights for coaches and analysts. Player performance metrics, such as running distances, player positioning, and actions like passes and goals, were automatically extracted and presented in an easy-to-understand format. The integration with a user-friendly interface enabled smooth interaction and real-time data visualization, significantly improving the efficiency of match analysis.

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APPENDIX
SAMPLE CODE

main.py

```
from utils import read_video, save_video
from trackers import Tracker
import cv2
import numpy as np
from team_assigner import TeamAssigner
from player_ball_assigner import PlayerBallAssigner
from camera_movement_estimator import CameraMovementEstimator
from view_transformer import ViewTransformer
from speed_and_distance_estimator import SpeedAndDistance_Estimator
import os
def main():
  try:
    # Define paths
    video_path = r"C:\Users\91763\Downloads\football_analysis-main
(1)\football_analysis-main\input_videos\input_video.mp4"
    model_path = r"C:\Users\91763\Downloads\football_analysis-main
(1)\football_analysis-main\models\best.pt"
    output_path = r"C:\Users\91763\Downloads\football_analysis-main
(1)\football_analysis-main\output_videos\output_video.avi"
    track_stub_path =r"C:\Users\91763\Downloads\football_analysis-main
(1)\football_analysis-main\stubs\track_stubs.pkl"
    camera_stub_path = r"C:\Users\91763\Downloads\football_analysis-main
(1)\football_analysis-main\stubs\camera_movement_stub.pkl"
```

```
if assigned_player != -1:
        player_track[assigned_player]['has_ball'] = True
        team_ball_control.append(player_track[assigned_player]['team'])
      else:
            team_ball_control.append(team_ball_control[-1] if team_ball_control else
None)
  except Exception as e:
    print("An error occurred:", str(e))
if __name__ == '__main__':
  main()
```

color_assignment.py:-

```
irom camera_movement_estimator import CameraMovementEstimator
from view_transformer import ViewTransformer
from speed_and_distance_estimator import SpeedAndDistance_Estimator

app = Flask(__name__)

# Define the path to the model (adjust this as needed)
MODEL_PATH = r"C:\Users\91763\Downloads\football_analysis-main
(1)\football_analysis-main\models\best.pt"
TRACK_STUB_PATH = r"C:\Users\91763\Downloads\football_analysis-main
(1)\football_analysis-main\stubs\track_stubs.pkl"
CAMERA_STUB_PATH = r"C:\Users\91763\Downloads\football_analysis-main
(1)\football_analysis-main\stubs\camera_movement_stub.pkl"

@app.route('/process_video', methods=['POST'])
def process_video():
  try:
    # Check if a video file was uploaded
    if 'video' not in request.files:
      return jsonify({"error": "No video file uploaded"}), 400
```

```
 team_ball_control = np.array(team_ball_control)

      # Draw Annotations
      print("Drawing annotations on frames...")
      output_video_frames = tracker.draw_annotations(video_frames, tracks, team_ball_control)
      output_video_frames =
camera_movement_estimator.draw_camera_movement(output_video_frames,
camera_movement_per_frame)
      speed_and_distance_estimator.draw_speed_and_distance(output_video_frames, tracks)

      # Save the annotated video to a temporary file
      with tempfile.NamedTemporaryFile(delete=False, suffix=".avi") as temp_output_file:
         output_path = temp_output_file.name
         save_video(output_video_frames, output_path)

      # Send the output video file as a response
      return send_file(output_path, as_attachment=True,
attachment_filename="output_video.avi")

   except Exception as e:
      return jsonify({"error": str(e)}), 500

   finally:
      # Clean up temporary files
      if os.path.exists(video_path):
         os.remove(video_path)
      if 'output_path' in locals() and os.path.exists(output_path):
         os.remove(output_path)

if __name__ == '__main__':
   app.run(debug=True)
```

Assigner.py

```
from sklearn.cluster import KMeans

class TeamAssigner:
  def __init__(self):
    self.team_colors = {}
    self.player_team_dict = {}
  def get_clustering_model(self,image):
    # Reshape the image to 2D array
    image_2d = image.reshape(-1,3)
    # Preform K-means with 2 clusters
    kmeans = KMeans(n_clusters=2, init="k-means++",n_init=1)
    kmeans.fit(image_2d)
    return kmeans
    def get_player_color(self,frame,bbox):
    image = frame[int(bbox[1]):int(bbox[3]),int(bbox[0]):int(bbox[2])]
    top_half_image = image[0:int(image.shape[0]/2),:]
    # Get Clustering model
    kmeans = self.get_clustering_model(top_half_image)
    # Get the cluster labels forr each pixel
    labels = kmeans.labels_
 # Reshape the labels to the image shape
clustered_image
labels.reshape(top_half_image.shape[0],top_half_image.shape[1])
 player_color = kmeans.cluster_centers_[player_cluster]

def assign_team_color(self,frame, player_detections):
    player_colors = []
    for _, player_detection in player_detections.items():
      bbox = player_detection["bbox"]
      player_color = self.get_player_color(frame,bbox)
      player_colors.append(player_color)
  def get_player_team(self,frame,player_bbox,player_id):
    if player_id in self.player_team_dict:
      return self.player_team_dict[player_id]

    player_color = self.get_player_color(frame,player_bbox)

    team_id = self.kmeans.predict(player_color.reshape(1,-1))[0]
    team_id+=1

    if player_id ==91:
      team_id=1

    self.player_team_dict[player_id] = team_id

    return team_id
```

Camera Movement.py

```
import pickle
import cv2
import numpy as np
import os
import sys
sys.path.append('../')
from utils import measure_distance,measure_xy_distance

class CameraMovementEstimator():
  def __init__(self,frame):
    self.minimum_distance = 5

    self.lk_params = dict(
      winSize = (15,15),
      maxLevel = 2,
elf.features = dict(
 maxCorners = 100,
 qualityLevel = 0.3,
 minDistance =3,
 blockSize = 7,
 mask = mask_features
 )
 def add_adjust_positions_to_tracks(self,tracks, camera_movement_per_frame):
 for object, object_tracks in tracks.items():
 for frame_num, track in enumerate(object_tracks):
 for track_id, track_info in track.items():
 position = track_info['position']
 camera_movement = camera_movement_per_frame[frame_num]
 position_adjusted = (position[0]-camera_movement[0],position[1]-camera_movement[1])
 tracks[object][frame_num][track_id]['position_adjusted'] = position_adjusted

 def get_camera_movement(self,frames,read_from_stub=False, stub_path=None):
 # Read the stub
 if read_from_stub and stub_path is not None and os.path.exists(stub_path):
 with open(stub_path,'rb') as f:
 return pickle.load(f)
 camera_movement = [[0,0]]*len(frames)
 old_gray = cv2.cvtColor(frames[0],cv2.COLOR_BGR2GRAY)
 old_features = cv2.goodFeaturesToTrack(old_gray,**self.features)
 for frame_num in range(1,len(frames)):
 frame_gray = cv2.cvtColor(frames[frame_num],cv2.COLOR_BGR2GRAY)
 new_features, _,_ =
cv2.calcOpticalFlowPyrLK(old_gray,frame_gray,old_features,None,**self.lk_params)
 max_distance = 0
 camera_movement_x, camera_movement_y = 0,0
 for i, (new,old) in enumerate(zip(new_features,old_features)):
 new_features_point = new.ravel()
 old_features_point = old.ravel()
 distance = measure_distance(new_features_point,old_features_point)
```

```
import sys
sys.path.append('../')
from utils import get_center_of_bbox, measure_distance

class PlayerBallAssigner():
    def __init__(self):
        self.max_player_ball_distance = 70

    def assign_ball_to_player(self,players,ball_bbox):
        ball_position = get_center_of_bbox(ball_bbox)

        miniumum_distance = 99999
        assigned_player=-1

        for player_id, player in players.items():
            player_bbox = player['bbox']

            distance_left = measure_distance((player_bbox[0],player_bbox[-1]),ball_position)
            distance_right = measure_distance((player_bbox[2],player_bbox[-1]),ball_position)
            distance = min(distance_left,distance_right)

            if distance < self.max_player_ball_distance:
                if distance < miniumum_distance:
                    miniumum_distance = distance
                    assigned_player = player_id

        return assigned_player
```

bbox_utils.py:-

```
def get_center_of_bbox(bbox):
  x1,y1,x2,y2 = bbox
  return int((x1+x2)/2),int((y1+y2)/2)
```

```
def get_bbox_width(bbox):
 return bbox[2]-bbox[0]
def measure_distance(p1,p2):
 return ((p1[0]-p2[0])**2 + (p1[1]-p2[1])**2)**0.5
def measure_xy_distance(p1,p2):
 return p1[0]-p2[0],p1[1]-p2[1]
def get_foot_position(bbox):
 x1,y1,x2,y2 = bbox
 return int((x1+x2)/2),int(y2)
```

Video_Utils.py:-

```
import cv2
def read_video(video_path):
  cap = cv2.VideoCapture(video_path)
  frames = []
  while True:
    ret, frame = cap.read()
    if not ret:
      break
    frames.append(frame)
  return frames

def save_video(ouput_video_frames,output_video_path):
  fourcc = cv2.VideoWriter_fourcc(*'XVID')
    out = cv2.VideoWriter(output_video_path, fourcc, 24, (ouput_video_frames[0].shape[1], 
ouput_video_frames[0].shape[0]))
  for frame in ouput_video_frames:
    out.write(frame)
  out.release()
```

View Transformer.py:-

```
import numpy as np
import cv2
```

```
class ViewTransformer():
def __init__(self):
court_width = 68
court_length = 23.32
self.pixel_vertices = np.array([[110, 1035],
[265, 275],
[910, 260],
[1640, 915]])
self.target_vertices = np.array([
[0,court_width],
[0, 0],
[court_length, 0],
[court_length, court_width]
])
self.pixel_vertices = self.pixel_vertices.astype(np.float32)
self.target_vertices = self.target_vertices.astype(np.float32)
self.persepctive_trasnformer = cv2.getPerspectiveTransform(self.pixel_vertices, self.target_vertices)
def transform_point(self,point):
p = (int(point[0]),int(point[1]))
is_inside = cv2.pointPolygonTest(self.pixel_vertices,p,False) >= 0
if not is_inside:
return None
reshaped_point = point.reshape(-1,1,2).astype(np.float32)
tranform_point = cv2.perspectiveTransform(reshaped_point,self.persepctive_trasnformer)
return tranform_point.reshape(-1,2)
def add_transformed_position_to_tracks(self,tracks):
for object, object_tracks in tracks.items():
for frame_num, track in enumerate(object_tracks):
for track_id, track_info in track.items():
position = track_info['position_adjusted']
position = np.array(position)
position_trasnformed = self.transform_point(position)
if position_trasnformed is not None:
position_trasnformed = position_trasnformed.squeeze().tolist()
tracks[object][frame_num][track_id]['position_transformed'] = position_trasnformed
```

Yolo Inference.py:-

```
from ultralytics import YOLO

model = YOLO(r"C:\Users\91763\Downloads\football_analysis-
main (1)\football_analysis-main\models\best.pt")

results=
model.predict(r"C:\Users\91763\Downloads\football_analysis-
main                                          (1)\football_analysis-
main\input_videos\input_video.mp4",save=True)
print(results[0])
print('=========================================='
)
for box in results[0].boxes:
   print(box)
```

Team Assigner.py:-

```
from sklearn.cluster import KMeans
class TeamAssigner:
   def __init__(self):
      self.team_colors = {}
      self.player_team_dict = {}

   def get_clustering_model(self,image):
      # Reshape the image to 2D array
      image_2d = image.reshape(-1,3)

      # Preform K-means with 2 clusters
      kmeans = KMeans(n_clusters=2, init="k-means++",n_init=1)
      kmeans.fit(image_2d)
```

```
def get_player_color(self,frame,bbox):
 image = frame[int(bbox[1]):int(bbox[3]),int(bbox[0]):int(bbox[2])]
 top_half_image = image[0:int(image.shape[0]/2),:]
 # Get Clustering model
 kmeans = self.get_clustering_model(top_half_image)
 # Get the cluster labels forr each pixel
 labels = kmeans.labels_
 # Reshape the labels to the image shape
 clustered_image = labels.reshape(top_half_image.shape[0],top_half_image.shape[1])
 # Get the player cluster
 corner_clusters =
[clustered_image[0,0],clustered_image[0,-1],clustered_image[-1,0],clustered_image[-1,-1]]
 non_player_cluster = max(set(corner_clusters),key=corner_clusters.count)
 player_cluster = 1 - non_player_cluster
 player_color = kmeans.cluster_centers_[player_cluster]
 return player_color
 def assign_team_color(self,frame, player_detections):

 player_colors = []
 for _, player_detection in player_detections.items():
 bbox = player_detection["bbox"]
 player_color = self.get_player_color(frame,bbox)
 player_colors.append(player_color)

 kmeans = KMeans(n_clusters=2, init="k-means++",n_init=10)
 kmeans.fit(player_colors)
 self.kmeans = kmeans
 self.team_colors[1] = kmeans.cluster_centers_[0]
 self.team_colors[2] = kmeans.cluster_centers_[1]
```

App.py:-

```
import streamlit as st
import cv2
import numpy as np
```

```
from utils.video_utils import save_video, read_video
from trackers import Tracker
from team_assigner import TeamAssigner
from player_ball_assigner import PlayerBallAssigner
from camera_movement_estimator import CameraMovementEstimator
from view_transformer import ViewTransformer
from speed_and_distance_estimator import SpeedAndDistance_Estimator

# Streamlit Custom CSS Styling for UI/UX
st.markdown("""
    <style>
    .main { background-color: #f0f2f6; }
    .stButton>button { background-color: #4CAF50; color: white; }
    .header-text { font-size: 28px; font-weight: 600; color: #4CAF50; }
    .metrics-box { border-radius: 5px; background-color: #e8f5e9; padding: 10px; margin-
bottom: 10px; }
    </style>
    """, unsafe_allow_html=True)

st.sidebar.image("path/to/football_logo.png", use_column_width=True)
st.sidebar.title("Football Analysis Dashboard")
st.sidebar.markdown("Analyze players, speed, and ball control in football videos with
advanced metrics.")

# File Upload Section
st.header("Football Analysis Video Upload")
st.markdown("<p class='header-text'>Upload your video to start analysis.</p>",
unsafe_allow_html=True)
        st.download_button(
            label="Download Annotated Video",
            data=open(output_path, "rb").read(),
            file_name="annotated_output_video.avi",
            mime="video/avi"
        )
```

OUTPUT SCREENSHOT

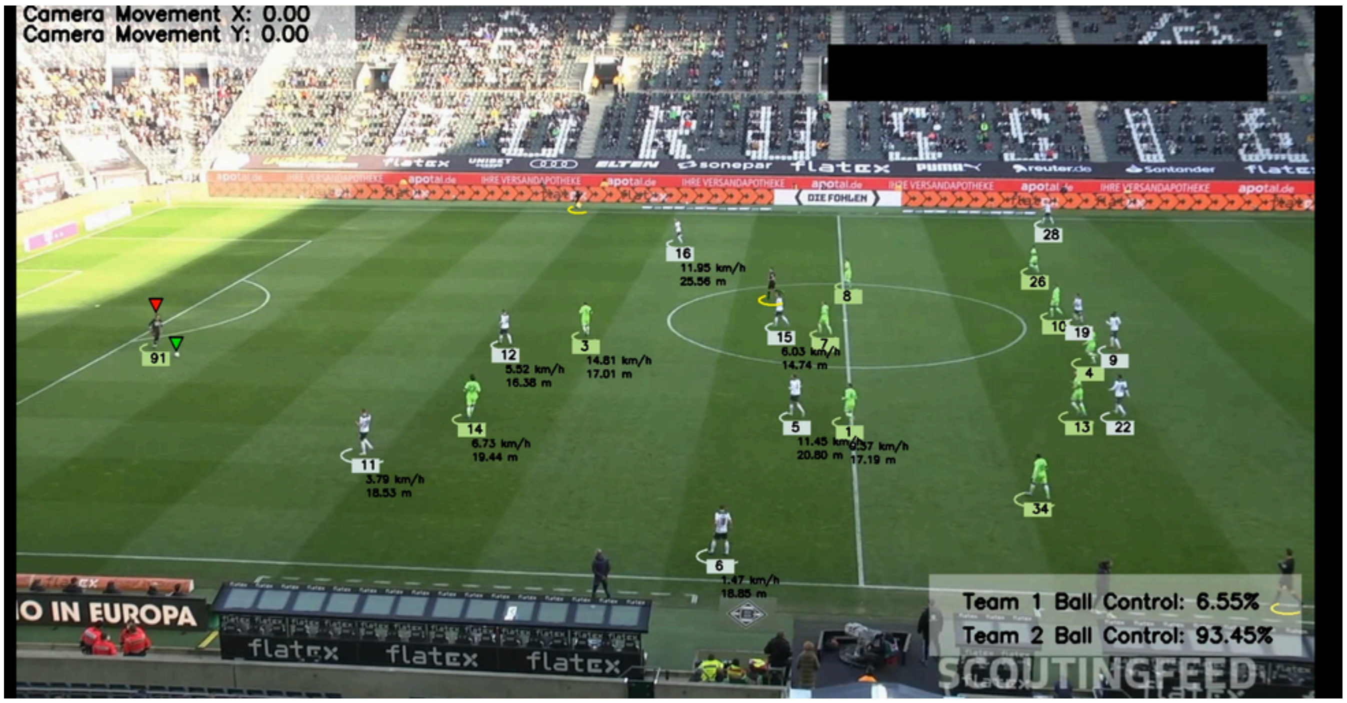

Fig 5.1 Output Screenshot of the Football Analysis

FOOTSAL: FOOTBALL ANALYSIS USING YOLO AND EAST

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Abstract **-**This paper presents a robust approach to analyzing football gameplay using YOLO (You Only Look Once) and EAST (Efficient and Accurate Scene Text) neural networks. The proposed system focuses on real-time player tracking, ball detection, and event recognition, leveraging advanced deep learning techniques for precise detection and analysis. While traditional methods often struggle with occlusion, overlapping players, and large-scale datasets, the combined use of YOLO and EAST significantly improves accuracy and efficiency. By utilizing pre-processed video footage segmented into frames, the system enables seamless player monitoring and strategy evaluation. This project demonstrates how computer vision can revolutionize football analysis for coaches, analysts, and enthusiasts.By automating the process of event recognition and player tracking, this project demonstrates the potential of computer vision in enhancing sports analytics, improving coaching strategies, and providing real-time feedback to analysts and fans.

Keywords: Football Analysis, YOLO, EAST, Computer Vision, Deep Learning, Object Detection, Sports Analytics

I. INTRODUCTION:-

Football, the world's most popular sport, generates immense interest in real-time analytics to evaluate player performance, team strategies, and match dynamics. Recent advancements in artificial intelligence (AI) have enabled the use of deep learning algorithms for analyzing complex sports datasets. Among the most prominent tools, YOLO excels at real-time object detection, while EAST specializes in text recognition and alignment.Traditional methods of football analysis often relied on manual annotation or basic image processing, which were time-consuming and error-prone. This paper proposes Footsal, an AI-driven system combining YOLO and EAST for comprehensive football analytics. The system tracks player movements, identifies the ball's trajectory, and recognizes critical events such as goals and fouls.

II. RELATED WORK:-

Existing techniques for football analysis have incorporated Convolutional Neural Networks (CNNs) for player detection and motion tracking. However, these methods often require extensive labeled datasets and lack real-time capability. YOLO, a single-a state-of-the-art object detection model, has significantly advanced sports analysis by providing real-time detection with high accuracy. On the other hand, EAST, a text detection algorithm, plays a critical role in recognizing player jersey numbers, an essential part of tracking individual player movements and statistics.Recent efforts have combined these models to enhance football analytics, but real-time analysis of both player movements and match events remains an ongoing challenge. This paper proposes an integrated system using YOLO for object detection and EAST for text recognition, providing a comprehensive solution for analyzing football matches in real-time.

III. PROBLEM STATEMENT:-

Football analysis has traditionally relied on manual observation, which can be time-consuming, prone to errors, and limited in scope. With the increasing amount of data available from live broadcasts and video recordings of football matches, there is a growing need for automated systems that can track players, detect key events, and analyze game dynamics in real-time.

The primary challenges in automating football analysis include:

Real-time Tracking: Football matches are fast-paced, and player movement is often occluded or overlapping, making it difficult to track players accurately in real-time.

IV. SYSTEM ARCHITECTURE AND DESIGN

The proposed system architecture for football match analysis is based on a deep learning framework, combining YOLO for object detection and EAST for text recognition. The system is designed to process video footage of football matches captured from various camera angles.

The core components of the system are as follows:YOLO-based Object Detection: The YOLO model is used to identify and track players and the ball throughout the video frames. The model's architecture enables rapid detection, making it suitable for real-time analysis of fast-moving objects like football players. YOLO identifies players, the ball, and other key objects, such as the goalposts,.EAST-based Text Recognition: EAST is used to detect and recognize text, such as the players' jersey numbers, from the video frames.

V. PROPOSED METHODOLOGY:-

The methodology for football analysis using YOLO and EAST can be summarized in the following steps:

Data Collection: Video footage from football matches is collected, with a focus on obtaining high-quality, high-resolution footage. The footage is pre-processed by splitting it into individual frames to make it suitable for real-time analysis.

Player and Ball Detection (YOLO): The YOLO model is applied to each frame to detect players and the ball.

Event Recognition: Accurately identifying key moments such as goals, assists, fouls, and offside calls remains a challenge, requiring precise tracking and context understanding.Additionally, traditional methods of player identification rely heavily on manual labeling or pose detection, which can be computationally expensive and slow. There is a need for an integrated, efficient system that combines the strengths of object detection (YOLO) and text recognition (EAST) to address these issues.

VI. IMPLEMENTATION AND RESULT

The implementation of the football analysis system was carried out using a combination of YOLO for object detection and EAST for text recognition. The following steps were undertaken to achieve the desired functionality:

Model Training and Data Preparation:

YOLO Model: The YOLOv5 model was chosen due to its high speed and accuracy in real-time object detection. A custom dataset of football match footage was compiled, including labeled frames of players, the ball, and other key objects like goalposts and the center circle.

EAST Model: The EAST text detector was trained on video frames with visible player jersey numbers. Preprocessing steps included grayscale conversion and normalization of image data to ensure optimal performance of both models.

The bounding boxes around players and the ball are used to track their movements across frames. The system processes the frames sequentially to track player positions and the ball's trajectory over time.Text Recognition (EAST): The EAST model is applied to the same frames to recognize and extract text data, such as player jersey numbers. This step allows the system to associate player movements with their respective identities, facilitating more accurate event detection.

VI. CONCLUSION AND FUTURE WORK

This paper proposed an integrated system for football analysis using YOLO and EAST, which successfully addresses the challenges of real-time tracking, ball detection, and event recognition. The use of YOLO for player and ball detection, combined with EAST for text recognition, enabled accurate and efficient analysis of football matches. The system was able to track players and the ball, identify key events, and provide real-time insights with high accuracy.Future improvements could involve training the models with more diverse datasets that include various lighting conditions, camera angles, and player actions. This would help the system to handle more complex and challenging scenarios, such as occlusions and fast-paced moments where players overlap.

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