REAL-TIME ANALYSIS AND ENHANCEMENT OF ATHLETE TRAINING BASED ON HAR, OPEN CV AND DEEP-LEARNING MODEL

Mini Project Report

Submitted in partial fulfillment of the requirements for the award of the Degree of

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In

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By

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ACE ENGINEERING COLLEGE

An Autonomous Institution

(NBA ACCREDITED B.TECH COURSES: EEE, ECE & CSE, ACCORDED NAAC 'A' GRADE)

(Affiliated to Jawaharlal Nehru Technological University, Hyderabad, Telangana)

Ghatkesar, Hyderabad – 501 301

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CERTIFICATE

This is to certify that the Mini Project work entitled **"REAL-TIME ANALYSIS AND ENHANCEMENT OF ATHLETE TRAINING BASED ON HAR, OPEN CV AND DEEP-LEARNING MODEL"** is being submitted by **Hiranmayi CH(21AG1A66F0), M Paul John(21AG1A66F9), P John Ricky(21AG1A66G6)** in partial fulfillment for the award of Degree of **BACHELOR OF TECHNOLOGY** in **DEPARTMENT OF CSE (ARTIFICIAL INTELLIGENCE & MACHINE LEARNING)** to the Jawaharlal Nehru Technological University, Hyderabad during the academic year 2024-25 is a record of bonafide work carried out by them under our guidance and supervision.

The results embodied in this report have not been submitted by the student to any other University or Institution for the award of any degree or diploma.

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DECLARATION

This is to certify that the work reported in the present project titled "**REAL-TIME ANALYSIS AND ENHANCEMENT OF ATHLETE TRAINING BASED ON HAR, OPEN CV AND DEEP-LEARNING MODEL**" is a record work done by us in the Department of CSE (Artificial Intelligence & Machine Learning), ACE Engineering College.

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ABSTRACT

This research focuses on analysis and enhancement of football players' techniques, aiming to refine critical aspects of their performance. By integrating advanced technologies such as Human Action Recognition (HAR), Artificial Intelligence (AI), and Deep Learning, the system evaluates players' movements and provides actionable feedback. The methodology focuses on improving shooting accuracy, optimal angles, and positioning, which are crucial for maximizing scoring potential and overall gameplay efficiency. Leveraging datasets derived from videos or photos of the players, the system identifies errors in technique and recommends adjustments to enhance performance. For example, it analyzes the player's shooting angle, highlights positions with higher scoring probabilities, and detects patterns that need improvement. This not only helps individual athletes refine their skills but also assists coaches in crafting strategies and optimizing man-marking tactics during matches. The analysis employs tools like OpenCV and Computer Vision to accurately measure movement dynamics, while advanced algorithms such as Artificial Neural Networks (ANNs) and YOLOv8, a state-of-the-art open-source computer vision library, extract and analyze relevant features. YOLOv8 is particularly effective due to its high precision in detecting and classifying attributes in real time. Python programming and open-source libraries form the backbone of the implementation, and development was conducted using IDEs such as Visual Studio Code and Google Colab. This system provides a holistic approach to improving football performance, enabling athletes and teams to achieve their goals through data-driven insights and personalized recommendations.

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CHAPTER 1

INTRODUCTION

The rapid advancements in artificial intelligence (AI) and computer vision technologies have transformed sports analytics, with football being a key area of impact. Athlete training and performance analysis, once reliant on subjective evaluations and manual tracking, now leverage the precision and scalability of AI-driven systems. Central to this evolution are convolutional neural networks (CNNs), which enable accurate analysis of player movements, team strategies, and game dynamics.

This work focuses on the assessment and subsequent improvement of key skills for football players, aiming to enhance critical aspects of their playing activities. By analyzing player movements using superior technologies like Human Activity Recognition (HAR), AI, and deep learning, the system provides actionable insights into shooting possibilities, angles, and positioning—factors that play a significant role in scoring and overall performance. Leveraging datasets derived from videos and images of players, the system identifies technical errors and recommends corrections to improve performance. For instance, it evaluates a player's shooting angles, highlights areas with a higher probability of success, and identifies behaviors requiring change. Such capabilities make the system effective not only in improving individual performance but also in refining strategies like man-to-man targeting during games.

For assessing mobility parameters, the study employs OpenCV and advanced computer vision techniques, ensuring high precision. To extract and determine additional features, outstanding algorithms like CNNs and YOLOv8 are utilized. YOLOv8, known for its real-time precision in detecting and classifying attributes, is particularly effective in processing game data efficiently. Python programming and open-source libraries form the core of the implementation, while development is carried out using IDEs such as Visual Studio Code and Google Colab.

By harnessing these advanced tools and methodologies, the system offers a transformative approach to athlete training and team performance optimization. It equips coaches and players with the insights needed to enhance gameplay, minimize errors, and achieve desired outcomes, revolutionizing the way football is played and analyzed in the modern era.

1.1 BACKGROUND AND CONTEXT OF THE PROJECT

1.1.1 WHAT IS CNN?

Convolutional Neural Networks (CNNs) are a specialized type of neural network designed to process structured grid-like data, such as images. The concept originated from biological vision systems, inspired by the work of Hubel and Wiesel in the 1960s, who discovered receptive fields in the cat's visual cortex. Yann LeCun developed the first CNN, called LeNet-5, in 1989 for handwritten digit recognition. CNNs work by applying convolutional filters to input data, extracting features like edges and textures, and building complex patterns layer by layer.

A CNN typically consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification or prediction. The non-linear activation functions, such as ReLU, introduce flexibility to learn non-linear relationships. CNNs gained prominence in the 2010s due to advancements in computation power and large datasets, leading to breakthroughs in tasks like image recognition and object detection. Modern architectures like AlexNet, VGG, and ResNet further improved performance, making CNNs a cornerstone of deep learning and computer vision applications.

The components of CNNs:

- Input Layer
- Convolutional Layer
- Activation Function
- Pooling Layer
- Fully Connected Layer (FC Layer)
- Output Layer

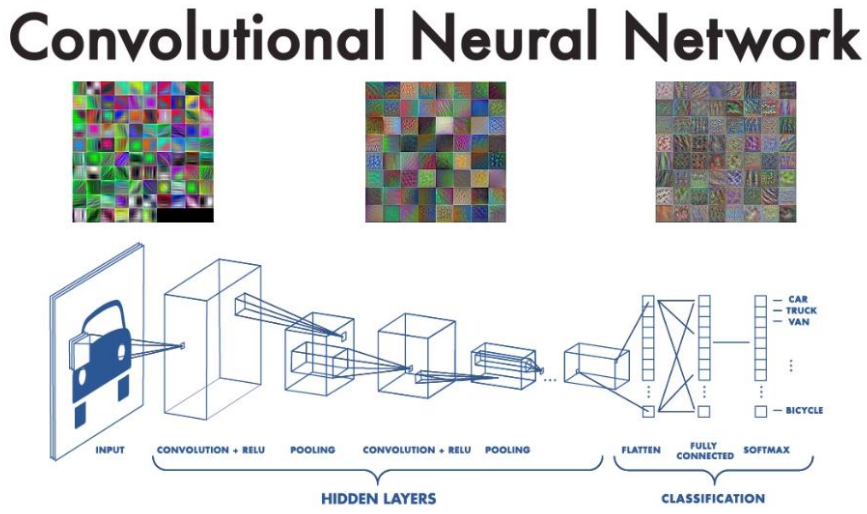


Fig 1.1: CNN

1. Input Layer

The input layer is the first component of a CNN and serves as the entry point for raw data, such as images or video frames. For image data, the input is typically a 3D array with dimensions corresponding to height, width, and the number of channels (e.g., RGB channels for color images). This layer does not perform any computation but simply passes the input data to the subsequent layers for processing. It is important to preprocess the input data, such as normalizing pixel values to a standard range (e.g., 0 to 1), to improve the network's efficiency and performance. The size of the input depends on the dataset and is fixed for each CNN architecture.

2. Convolutional Layer

The convolutional layer is the core building block of a CNN, responsible for extracting features from the input data. It applies convolution operations using filters (kernels) that slide across the input matrix, computing dot products between the filter weights and the input values in each receptive field. This produces feature maps that highlight patterns, such as edges, corners, and textures. Multiple filters can be used to extract different features from the same input.

The parameters of the filters are learned during training, allowing the network to adapt to specific patterns in the data. The convolutional layer reduces computational complexity compared to fully connected networks, as it reuses the same filter across the input, introducing spatial hierarchies.

3. Activation Function

The activation function introduces non-linearity into the CNN, enabling it to model complex relationships in the data. Without non-linear activation, the network would behave like a linear model, which limits its capacity to solve intricate problems. The most commonly used activation function in CNNs is the Rectified Linear Unit (ReLU), which sets all negative values in the feature map to zero while retaining positive values. This simplicity improves computational efficiency and helps avoid the vanishing gradient problem. Other activation functions, such as Sigmoid and Tanh, can also be used, but ReLU is preferred due to its effectiveness in deep networks. Activation functions are applied element-wise to the feature maps generated by convolutional layers.

4. Pooling Layer

The pooling layer is a down-sampling operation that reduces the spatial dimensions of the feature maps, making the model computationally efficient and less prone to overfitting. It aggregates features in small regions, typically using Max Pooling or Average Pooling. Max Pooling selects the maximum value from a region, emphasizing the most prominent features, while Average Pooling computes the average value, providing a smoother representation. Pooling layers help the network become invariant to small transformations, rotations, and scaling in the input data. By preserving essential features while discarding redundant information, pooling layers contribute to the model's ability to generalize well to unseen data.

5. Fully Connected Layer (FC Layer)

The fully connected layer connects all neurons from the previous layer to every neuron in the current layer, mimicking traditional feedforward neural networks. Before feeding data into the FC layer, feature maps are flattened into a 1D vector. The FC layer aggregates features learned in earlier layers

and maps them to the final output, such as class probabilities for classification tasks or continuous values for regression tasks. The weights of the FC layer are learned during training, and its size depends on the number of output classes or dimensions. This layer often acts as the decision-making part of the CNN, combining high-level features to make accurate predictions.

6. Output Layer

The output layer provides the final predictions based on the task. For classification problems, it uses activation functions like Softmax to output a probability distribution over classes. For regression tasks, the output is typically a single continuous value or a vector of values without additional activation. The number of neurons in the output layer corresponds to the number of target classes in a classification task or the dimensions of the output in regression. This layer is where the network's predictions are compared with the ground truth during training, and the error is computed using a loss function, which is then backpropagated to adjust the network's weights.

These layers together pipeline the working of CNN in effective way, helping to identify, detect the objects using photos, and video frames.

HOW TO TRAIN CNNs:

Training a Convolutional Neural Network (CNN) involves several well-defined steps, starting from preparing the dataset to optimizing the model for accurate predictions. The process begins with **data collection and preprocessing**, which is crucial for achieving robust performance. Datasets should represent the target task comprehensively, including diverse samples of the objects or patterns the model is expected to learn. Preprocessing involves resizing images to a consistent dimension, normalizing pixel values, and augmenting the data to increase variety. Techniques like flipping, rotating, cropping, and adjusting brightness help make the model resilient to real-world variations.

Once the data is ready, the next step is to **design the CNN architecture**. A CNN typically consists of convolutional layers, pooling layers, and fully connected layers. Convolutional layers extract features such as edges, textures, and patterns, while pooling layers reduce spatial dimensions, retaining essential information and improving computational efficiency. Fully connected layers combine the extracted features to make predictions. Choosing the right architecture is crucial; simpler architectures may suit small datasets, while deeper networks like ResNet or VGG are better for more complex tasks.

The third step involves **training the network using forward and backward propagation**. During the forward pass, input data flows through the network, generating predictions. The difference between these predictions and the actual labels, measured using a loss function such as cross-entropy or mean squared error, quantifies the model's error. In the backward pass, gradients of the loss function are calculated with respect to the model's parameters using backpropagation. These gradients are used to update the parameters iteratively through an optimization algorithm like stochastic gradient descent (SGD) or Adam, aiming to minimize the loss and improve the model's predictions over time.

In addition to the primary training steps, continuously monitoring the CNN’s performance during training is crucial to ensure it learns effectively. Tools like TensorBoard help track metrics such as loss, accuracy, and gradient trends over epochs, providing insights into potential issues like overfitting or stagnation. Data augmentation techniques can be applied dynamically during training to introduce variations and improve the model’s robustness to unseen data. Fine-tuning hyperparameters, such as the learning rate, batch size, and the number of convolutional filters, often significantly improves model performance. Using adaptive optimizers like Adam or RMSprop and implementing learning rate

schedulers can help the network converge faster and more efficiently. Leveraging GPUs or TPUs for computation speeds up the training process, allowing for the handling of larger datasets and more complex architectures. After training, the model can be saved and deployed for various tasks, including image classification, object detection, or real-time applications, ensuring its practical usability.

Evaluating and fine-tuning a Convolutional Neural Network (CNN) is crucial for ensuring it generalizes well to new, unseen data. After training, the model's performance is tested on a separate validation or test dataset using metrics like accuracy, precision, recall, and F1 score. These metrics provide insights into different aspects of the model's performance, with precision and recall being especially important for imbalanced datasets. Techniques like early stopping, learning rate adjustment, and regularization (e.g., dropout, weight decay) help prevent overfitting. Early stopping halts training when performance degrades on the validation set, while learning rate adjustments ensure better convergence.

Transfer learning is another effective strategy, where a pre-trained CNN is fine-tuned for a specific task, reducing the need for large labeled datasets. Hyperparameter tuning, using methods like grid search or Bayesian optimization, further optimizes model performance. By combining these techniques, CNNs can achieve high accuracy and robustness, ensuring strong performance on real-world data while avoiding overfitting. The goal is to balance accuracy with generalization, making the model effective across various scenarios.

Types of CNNs:

a) **LeNet-5**
b) **VGGNet**
c) **AlexNet**

LeNet-5

LeNet-5 is one of the earliest Convolutional Neural Networks (CNNs), developed by Yann LeCun and his collaborators in 1998. It was primarily designed for handwritten digit recognition and played a foundational role in demonstrating the potential of deep learning for image processing tasks. LeNet-5 laid the groundwork for modern CNN architectures.

Structure of LeNet-5:

LeNet-5 has a relatively simple architecture with the following components:

1. **Input Layer**: Accepts 32x32 grayscale images.
2. **Convolutional Layers**: Two convolutional layers (C1 and C3) with different numbers of filters (6 and 16, respectively) to extract features.
3. **Pooling Layers**: Two average pooling (subsampling) layers (S2 and S4) to reduce spatial dimensions.
4. **Fully Connected Layers**: Three fully connected layers (F5, F6, and output layer), with the final layer performing classification.
5. **Activation Functions**: Sigmoid or tanh activations were used due to the period's prevalent practices.

Applications Of LeNet-5:

1. **Handwritten Digit Recognition**:
   LeNet-5 was designed for recognizing handwritten digits, such as those in the MNIST dataset. It could distinguish numbers with high accuracy, making it ideal for digitized record-keeping systems.
2. **Optical Character Recognition (OCR)**:
   Its ability to analyze and interpret text from scanned documents made it valuable in OCR systems for converting images of text into machine-readable formats.
3. **License Plate Recognition**:
   LeNet-5 was applied in early systems for detecting and recognizing characters on license plates, assisting in traffic management and security systems.
4. **Postal Automation**:
   It helped automate the sorting of mail by recognizing handwritten or printed postal codes, significantly improving efficiency in postal services.
5. **Medical Imaging**:
   In simple medical imaging tasks, LeNet-5 could detect patterns such as anomalies in grayscale scans.

Challenges Faced By LeNet-5:

1. **Scalability**:
   LeNet-5 struggles with large and high-resolution color images, as it was designed for low-complexity tasks.
2. **Lack of Depth**:
   Its shallow architecture limits its ability to learn complex features from intricate datasets, leading to lower accuracy on modern tasks.
3. **Inefficient for Diverse Applications**:
   LeNet-5 is unsuitable for applications requiring advanced feature hierarchies, such as facial recognition or object detection.
4. **Overfitting**:
   Without modern regularization techniques like dropout, LeNet-5 could overfit on smaller datasets.
5. **Obsolete Performance**:
   Compared to contemporary architectures, it lacks optimization techniques such as ReLU activations, batch normalization, and residual connections, which boost efficiency and performance.

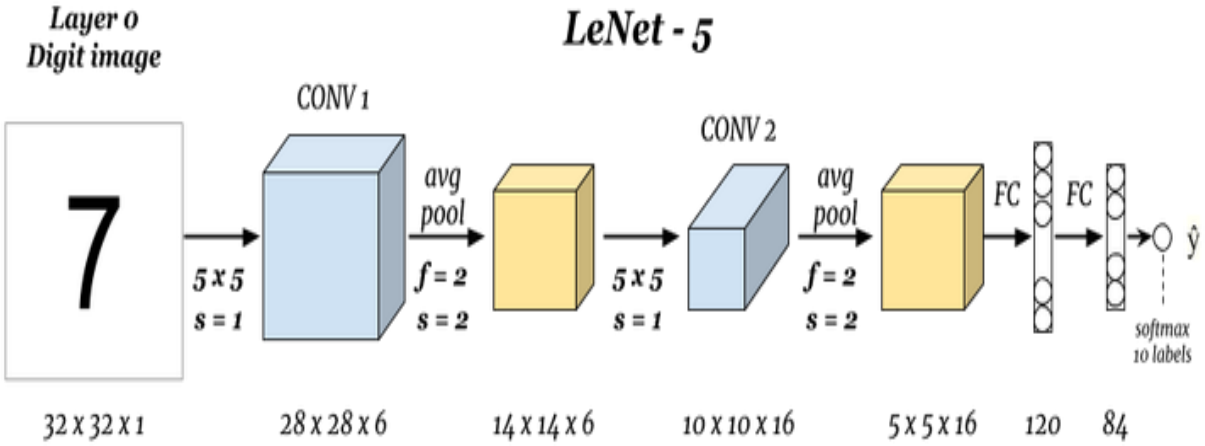


Fig 1.2: LeNet-5

VGGNet

VGGNet, developed by the Visual Geometry Group at the University of Oxford in 2014, is known for its simplicity and uniform structure. VGGNet demonstrated the importance of depth in CNNs for feature extraction and significantly influenced subsequent architectures.

Structure Of VGGNet:

VGGNet's structure is characterized by:

1. **Input Layer**: Takes 224x224 RGB images.
2. **Convolutional Layers**: Uses small 3x3 convolutional kernels across all layers, stacked to increase network depth.
3. **Pooling Layers**: Max pooling is applied after specific convolutional layers to downsample feature maps.
4. **Fully Connected Layers**: Three dense layers, with the final layer producing class probabilities using softmax.
5. **Activation Functions**: ReLU activations introduce non-linearity, preventing vanishing gradients.
6. **Variants**: VGG-16 and VGG-19, with 16 and 19 layers, respectively, are the most common variants.

Applications Of VGGNet:

1. **Image Classification**:
   VGGNet became famous for its performance in image classification tasks, particularly in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC).
2. **Feature Extraction for Transfer Learning**:
   Its deep layers are widely used for transfer learning, where pretrained models are fine-tuned for specific applications like facial recognition or plant disease detection.
3. **Object Detection**:
   VGGNet serves as a backbone for object detection models like R-CNN and Fast R-CNN, helping detect and classify objects in images and videos.

4. **Style Transfer**:
   VGGNet's convolutional layers extract deep features, making it suitable for artistic style transfer, where one image's texture is applied to another.
5. **Medical Imaging**:
   The network is used in medical fields to detect anomalies in X-rays, CT scans, and MRIs, providing diagnostic support in healthcare.

Challenges Faced By VGGNet:

1. **High Computational Requirements**:
   VGGNet requires substantial memory and computational power due to its large number of parameters and layers.
2. **Redundancy in Parameters**:
   The excessive parameters can lead to overfitting, making it less efficient for smaller datasets.
3. **Slow Training and Inference**:
   The depth and design of the network increase the time required for both training and inference compared to lighter models.
4. **Inefficiency for Real-Time Applications**:
   Due to its computationally intensive nature, VGGNet is unsuitable for real-time tasks like autonomous driving or live video analysis.
5. **Lack of Innovation in Design**:
   Unlike modern networks with features like residual connections (as in ResNet), VGGNet relies on a straightforward stacking of layers, which limits its adaptability and efficiency.

AlexNet

AlexNet is a groundbreaking convolutional neural network (CNN) architecture that marked a turning point in deep learning and computer vision. Introduced by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012, it won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) by a significant margin, achieving top-5 error rates that were almost half of the runner-up. AlexNet introduced several innovations, including ReLU activation functions, dropout for regularization, and GPU utilization for efficient training. It paved the way for the development of deeper and more complex

neural networks by demonstrating the scalability and effectiveness of deep learning for image classification tasks.

Structure of AlexNet

AlexNet consists of eight layers: five convolutional layers and three fully connected layers. Below is an overview of its architecture:

1. **Input Layer**:
    - Input size: 227×227×3227 \times 227 \times 3227×227×3 (RGB images).
2. **Convolutional Layers**:
    - **Conv1**: 96 filters of size 11×1111 \times 1111×11, stride 4, followed by ReLU activation and max pooling.
    - **Conv2**: 256 filters of size 5×55 \times 55×5, stride 1, followed by ReLU activation and max pooling.
    - **Conv3**: 384 filters of size 3×33 \times 33×3, stride 1, with ReLU activation.
    - **Conv4**: 384 filters of size 3×33 \times 33×3, stride 1, with ReLU activation.
    - **Conv5**: 256 filters of size 3×33 \times 33×3, stride 1, followed by ReLU activation and max pooling.
3. **Fully Connected Layers**:
    - **FC6**: Fully connected with 4,096 neurons and ReLU activation.
    - **FC7**: Fully connected with 4,096 neurons and ReLU activation.
    - **FC8 (Output Layer)**: Fully connected with the number of neurons equal to the number of classes, followed by a Softmax activation for classification.
4. **Regularization**:
    - **Dropout**: Applied to FC6 and FC7 layers to reduce overfitting.
5. **GPU Utilization**:
    - The model was trained using two GPUs, with layers divided between them to optimize computational efficiency.

Applications of AlexNet

AlexNet revolutionized computer vision by demonstrating the power of deep learning, and its applications extend across various fields:

1. **Image Classification**:
   AlexNet's ability to classify images into categories has been applied in object detection, autonomous vehicles, and medical image diagnostics.
2. **Transfer Learning**:
   Pretrained AlexNet models have been used in transfer learning for tasks such as plant disease detection, facial recognition, and anomaly detection in industrial systems.
3. **Medical Imaging**:
   AlexNet has been employed to detect and classify diseases in X-rays, CT scans, and other medical imaging modalities, aiding in faster and more accurate diagnostics.
4. **Surveillance Systems**:
   Its image recognition capabilities are used in security systems to identify objects, detect anomalies, and monitor activities in real time.
5. **Content-Based Image Retrieval (CBIR)**:
   AlexNet is used to develop systems that retrieve images based on visual content, improving search engines and e-commerce platforms.

Challenges Faced by AlexNet

While AlexNet set a new benchmark for deep learning, it faces several challenges:

1. **Computational Complexity**:
   Training AlexNet requires significant computational resources, including high-end GPUs. The dual-GPU requirement made it less accessible for researchers with limited resources.
2. **Overfitting**:
   Despite dropout regularization, AlexNet has a high number of parameters (~60 million), making it prone to overfitting, especially when trained on smaller datasets.

3. **Inefficiency for Modern Standards**:

   The use of large filters in the initial convolutional layers (e.g., 11×1111 \times 1111×11) results in inefficient feature extraction compared to modern architectures like VGGNet and ResNet, which use smaller filters for better performance.

4. **Inflexibility with Large-Scale Data**:

   While AlexNet performs well on relatively small datasets like ImageNet, it struggles with scalability for larger and more diverse datasets without modifications.

5. **Lack of Advanced Features**:

   AlexNet lacks innovations such as skip connections (found in ResNet) or depthwise separable convolutions (used in MobileNet), which improve efficiency and accuracy in modern architectures.

AlexNet's historical significance lies in its pioneering role, but its design has been surpassed by newer architectures that address these limitations while building on its core principles.

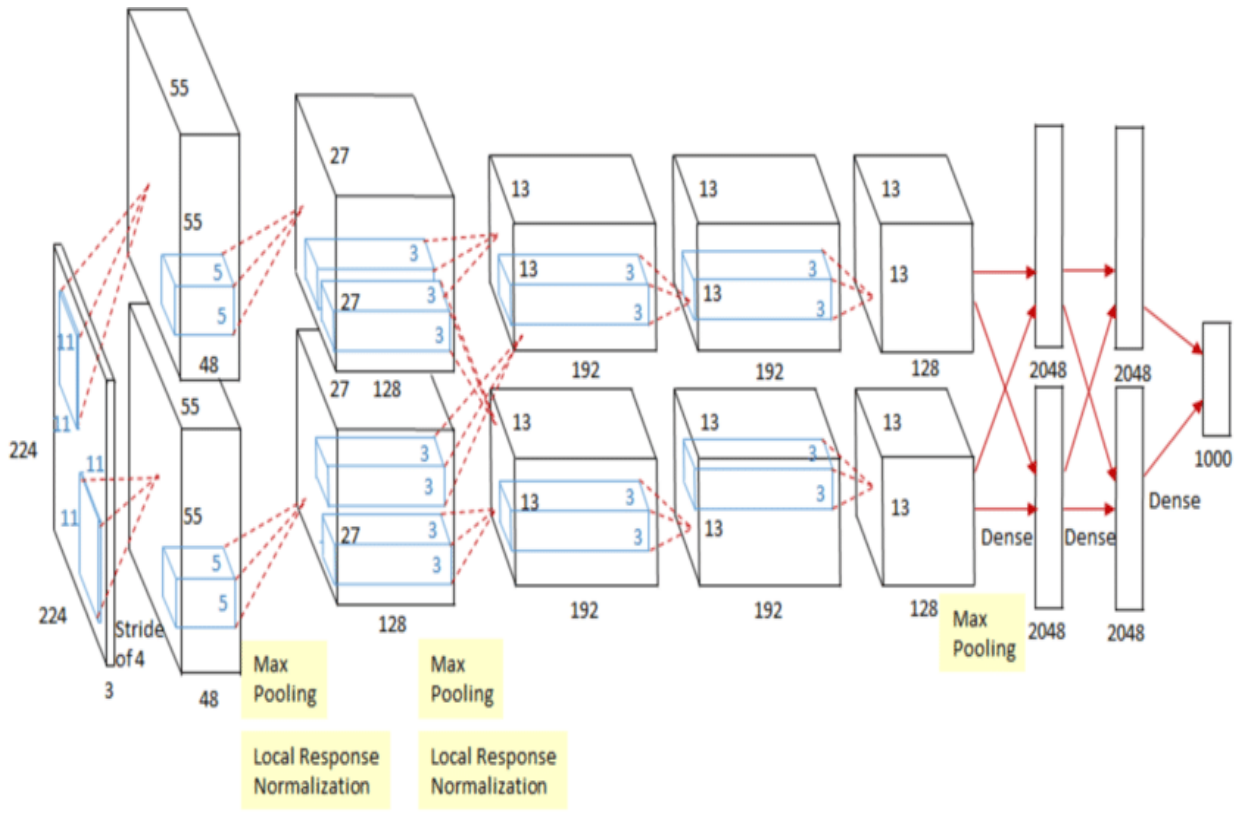


Fig.1.3: AlexNet

1.1.2 What is Yolo?

YOLO (You Only Look Once) is a real-time object detection algorithm designed to efficiently identify objects in images or videos. It differs from traditional methods by processing an entire image in a single pass through a neural network, predicting bounding boxes and class probabilities simultaneously. YOLO divides the input image into a grid, where each cell is responsible for detecting objects within its bounds. This approach enables the algorithm to detect objects quickly, making it suitable for applications that require high-speed processing, such as autonomous vehicles, video surveillance, and sports analytics.

YOLO's architecture uses a unified model to handle object detection as a regression problem, ensuring both speed and accuracy. The algorithm predicts multiple bounding boxes and their confidence scores in real-time, reducing the computational overhead. Over successive versions, including YOLOv8, enhancements have been made to improve detection precision, handle complex object scenarios, and optimize inference time. Its ability to detect multiple objects simultaneously, combined with its lightweight design, makes YOLO a widely used and versatile solution for various computer vision tasks.

Yolo is a special type of deep learning based object detection model, used to identify and classify the objects from a given image or a video frame. This classification is done by training the model and it identifies objects using RGB colors in the image.

What is Deep-Learning Based Object Detection?

Deep learning-based object detection is a cutting-edge approach in computer vision that combines the capabilities of convolutional neural networks (CNNs) and deep learning algorithms to detect and localize objects within images or videos. Unlike traditional detection methods that rely on handcrafted features and shallow learning models, deep learning enables automated feature extraction, making the process more accurate and scalable. The system works by classifying objects and predicting their locations using bounding boxes. These models learn hierarchical patterns, allowing them to identify even complex and subtle features of objects. The core advantage lies in their ability to adapt to diverse scenarios, such as varying lighting, perspectives, and object occlusions.

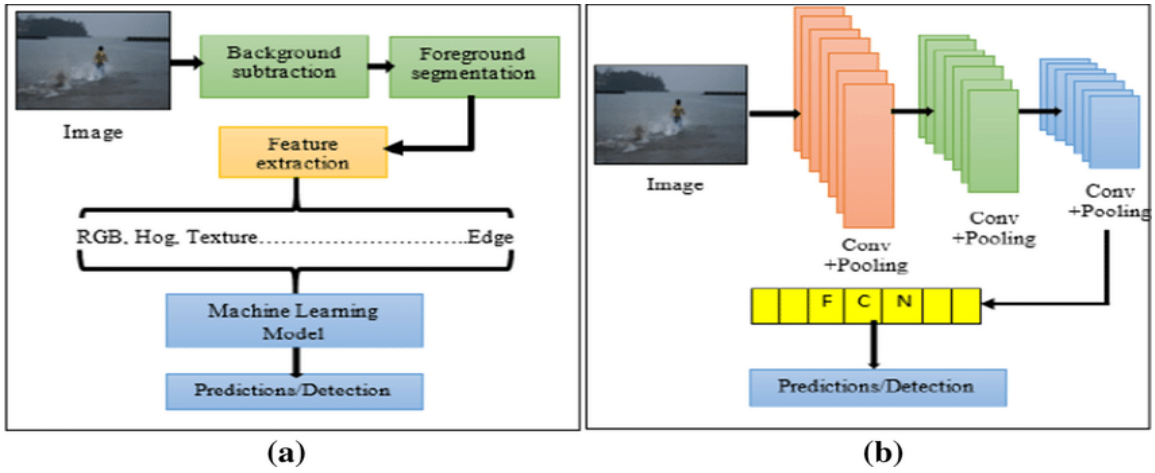


Fig 1.4 : Deep learning vs Yolo

Object detection algorithms in deep learning are categorized into two main types: single-stage and two-stage detectors. Single-stage detectors, like YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector), combine classification and localization into a single pass, prioritizing speed for real-time applications. On the other hand, two-stage detectors like Faster R-CNN first generate region proposals, then refine these to classify objects and predict accurate bounding boxes. While two-stage detectors are known for their higher accuracy, single-stage detectors are preferred for tasks requiring fast inference. Advanced techniques, such as feature pyramids, attention mechanisms, and multi-scale detection, further enhance these models' performance.

Deep learning-based object detection has transformed applications across industries. In autonomous vehicles, it helps identify pedestrians, vehicles, and road signs to ensure safe navigation. In healthcare, it detects anomalies in medical imaging, such as tumors in X-rays or MRIs. Retailers use it for inventory management by detecting and counting products. Sports analytics leverage these models for tracking players and equipment during matches, while surveillance systems utilize them for identifying people and monitoring activities. The adaptability, precision, and scalability of deep learning-based object detection make it an indispensable tool in solving complex visual recognition problems. As Yolo being a part of the Deep learning object detection algorithm, both are having similar kind of system structure but yolo has a slight technological advancement, this shows how the technology advancement is taking place.

Why Yolo's?

YOLO (You Only Look Once) is a powerful tool for athlete training because it allows for real-time, precise movement analysis, providing valuable insights into performance and technique. By leveraging YOLO's object detection capabilities, athletes and coaches can track movements, refine skills, and identify potential injury risks during training sessions. Its ability to analyze large amounts of video data quickly and accurately makes it a game-changer in sports training, offering an objective, data-driven approach to improvement.

1. Real-time Movement Tracking

Traditional training often relies on delayed feedback or subjective observations, which can slow down the improvement process. YOLO allows real-time analysis, enabling coaches and athletes to instantly observe and correct techniques during training sessions. This immediate feedback helps athletes make on-the-spot adjustments, accelerating learning and reducing mistakes. By processing video footage in real-time, YOLO identifies key movements and patterns as they occur. This allows coaches to observe precise details like jump height, running speed, or hand positioning, ensuring that any issues are addressed immediately rather than after the session.

2. Enhanced Performance Analysis

Sports performance often involves subtle, complex movements that are difficult to assess manually. YOLO can break down these movements in detail, allowing coaches to pinpoint areas for improvement that may not be immediately obvious to the naked eye. YOLO's object detection capabilities can track multiple body parts or entire body movements in high detail, analyzing biomechanics such as stride length, posture, and arm swing. This data provides coaches with specific information on how athletes can refine their technique for improved efficiency and effectiveness in their sport.

3. Injury Prevention

Injuries often arise from poor technique, overuse, or incorrect body mechanics. By detecting early signs of stress or biomechanical inefficiencies, YOLO can help prevent injuries before they happen,

reducing downtime for athletes and increasing their longevity in their sport. YOLO analyzes patterns in an athlete's movements and flags any irregularities, such as asymmetry, excessive strain on joints, or inefficient posture. By tracking changes over time, coaches can detect signs of fatigue or improper form that may lead to injury, allowing for proactive intervention, such as modifying training intensity or suggesting corrective exercises.

4. Multi-Athlete Tracking

In team sports, analyzing the movements of individual athletes within the context of a group is crucial for optimizing strategies and improving team dynamics. YOLO's ability to track multiple athletes simultaneously offers insights into player positioning, team coordination, and interaction. YOLO can detect and track multiple players within a single frame, analyzing how each athlete moves relative to others. In sports like soccer, basketball, or football, this allows coaches to assess positioning, timing, and decision-making, helping athletes improve their teamwork, spatial awareness, and tactical execution.

5. Objective Data for Decision Making

Traditional training feedback can sometimes be subjective, relying on coaches' opinions or limited data points. YOLO provides objective, data-driven insights, helping coaches make more informed decisions and track progress more accurately. YOLO analyzes video data to provide quantifiable metrics, such as movement speed, distance covered, or angles of motion. These metrics can be tracked over time, offering clear evidence of improvement or areas that require more work. This objective feedback ensures that training decisions are based on facts rather than intuition, leading to more consistent and effective performance enhancements.

Applications of Yolo

1. Real-Time Object Detection in Sports Training

YOLO is used in sports training for real-time tracking of athletes' movements, such as running, jumping, or sprinting. It helps coaches provide immediate feedback on technique, posture, or stride length, allowing athletes to make instant adjustments. This is especially useful in individual sports, where precise movement analysis is critical for improving performance and preventing injury.

2. Automated Surveillance and Security

In security applications, YOLO enables real-time object detection in video surveillance, identifying people, vehicles, and unusual activities. Its ability to track multiple objects at once makes it ideal for monitoring public spaces, parking lots, or airports, alerting security teams to potential threats quickly and efficiently.

3. Autonomous Vehicles and Traffic Monitoring

YOLO is essential for autonomous vehicles, helping them detect and classify objects like pedestrians, other vehicles, and road signs in real-time. It enables self-driving cars to navigate safely by avoiding collisions and adhering to traffic rules. Additionally, YOLO can be used in traffic monitoring systems to track vehicles and manage urban traffic flow effectively.

1.1.3 Athlete Training Analysis

Athlete training analysis is vital for improving performance, preventing injuries, and ensuring long-term athletic development. By closely monitoring an athlete's movements and biomechanics, coaches can identify flaws or inefficiencies in technique that may hinder performance or lead to injury. This allows for the creation of customized training plans that target specific areas of improvement, whether it's posture, strength, or agility. Regular analysis provides athletes with immediate feedback, enabling them to make adjustments during training and accelerate their progress. Additionally, it helps identify early signs of fatigue or overuse, allowing for timely interventions that reduce the risk of injury. Overall, athlete training analysis enhances training precision, supports recovery, and promotes sustained performance gains, ensuring athletes can perform at their best while minimizing the risk of setbacks.

1.1.3.1 Issue with Previous Approach

Relying solely on YOLO (You Only Look Once) for athlete training analysis has become outdated due to significant advancements in technology and deep learning models. While YOLO was once a popular choice for object detection, it struggles with several limitations in the context of modern sports training. One major issue is that newer models, such as YOLOv8, EfficientDet, and Detectron2, have surpassed YOLO in terms of accuracy, speed, and precision, offering better performance, especially

in detecting fine details and handling complex scenes. Additionally, earlier implementations of YOLO often used low-resolution cameras, which resulted in blurry, pixelated images, making it difficult to accurately assess athletic movements such as posture, stride, or technique. As camera technology has improved, higher-resolution video allows for much clearer and more detailed analysis. Moreover, YOLO's ability to detect and track objects in crowded or dynamic environments, like team sports, is limited, as it struggles with identifying individual players when they are close together or moving quickly. More advanced models now incorporate features such as spatial attention and temporal consistency, enabling them to track athletes more effectively in fast-paced situations. Another key limitation is YOLO's lack of adaptability to different sports or specific training contexts; earlier models were not fine-tuned for specialized tasks like motion analysis. In contrast, modern deep learning models are designed to be more flexible, allowing for better performance across various sports and environments. Finally, YOLO's focus on static object detection in individual frames limits its ability to understand the temporal nature of athletic movements. Newer models, such as 3D CNNs and video analysis networks, offer a better grasp of movement evolution over time, making them far more suitable for dynamic, performance-based analysis.

In summary, while YOLO was a pioneering tool, its outdated features and limitations make it less effective compared to the advanced, specialized models now available for athlete training enhancement.

1.1.3.2 Introducing CNN models into Athlete training

The use of advanced CNN models like YOLOv8 (You Only Look Once version 8) and HAR (Human Activity Recognition) is revolutionizing athlete training by providing detailed, real-time analysis of athletic movements. YOLOv8, a state-of-the-art object detection model, can track athletes' movements during live action through sensors and cameras placed in training environments. It can analyze key aspects of performance, such as posture, stride, and biomechanics, by processing video footage.

In sports like basketball or soccer, YOLOv8 can track player positions, detect specific gestures (e.g., jumps or sprints), and identify motion inefficiencies. This allows coaches to provide immediate feedback and make adjustments to optimize technique and performance. YOLOv8's ability to detect and track multiple players simultaneously makes it especially useful for team sports, where analyzing interactions between athletes is crucial.

Similarly, Human Activity Recognition (HAR) models, which use CNNs to classify and interpret physical activities, play a vital role in enhancing training. HAR models leverage data from wearable sensors and cameras to monitor and evaluate an athlete's movements, identifying specific actions like running, lifting, or jumping. By analyzing this data, HAR can assess the quality and intensity of these activities, helping coaches tailor workouts and detect early signs of fatigue or improper form. The combination of HAR and sensor-based data allows for personalized, data-driven training plans that adapt to the athlete's needs and reduce the risk of injury. Together with video cameras and motion sensors, YOLOv8 and HAR offer a highly accurate, real-time solution for movement analysis, performance optimization, and injury prevention, ensuring a more efficient and targeted approach to athletic development.

1.1.3.3 Leveraging CNN and Deep Learning Models to Revolutionize Athlete Training

The introduction of Convolutional Neural Networks (CNNs) and deep learning models into athlete training represents a transformative shift in how sports performance is analyzed, improved, and optimized. Traditional training methods often rely on coach expertise, manual analysis, and subjective assessments, but deep learning offers data-driven insights that can greatly enhance training regimens and athlete development.

CNNs, in particular, are highly effective for tasks such as video analysis, movement tracking, and injury prevention. By processing large datasets of visual inputs (such as video footage of an athlete's movements), CNNs can identify patterns in an athlete's biomechanics, posture, and technique that might be difficult for human coaches to spot. This level of detailed analysis allows for more precise adjustments to training programs, targeting specific aspects of performance that need improvement. For instance, in sports like tennis, basketball, or swimming, CNNs can analyze subtle movements like swing angles, body posture, and stride length to optimize technique and improve overall efficiency

Football is a globally celebrated sport where even minor improvements in technique can significantly influence a player's performance and a team's success. Traditionally, player evaluation and training have relied on manual observation and basic video analysis, which are time-consuming and often subjective. With the advent of technology, automated systems have emerged to assist in performance analysis, but many of these systems are limited in their scope, focusing primarily on basic tracking and positional data. They lack the ability to provide in-depth analysis of critical aspects such as shooting angles, positioning, and movement patterns.

Recent advancements in Artificial Intelligence (AI), Computer Vision, and Deep Learning have created opportunities to overcome these limitations. Technologies like YOLO (You Only Look Once) have been used for real-time object detection, while Convolutional Neural Networks (CNNs) and other deep learning models are increasingly applied to recognize patterns and extract detailed features from data. Integrating these technologies offers a way to build a more comprehensive system capable of analyzing player techniques, detecting errors, and delivering actionable insights. This project leverages these advancements to address the growing demand for data-driven performance analysis in football, enabling players to enhance their skills and teams to refine strategies based on objective, real-time feedback.

1.2 PROBLEM STATEMENT AND OBJECTIVE

Football performance analysis is often constrained by manual methods or basic automated systems, which lack the capability to accurately evaluate and refine player techniques. Current approaches, including those based solely on YOLO for object detection or standard video analysis, fall short in addressing crucial performance metrics such as shooting precision, optimal positioning, and detailed movement analysis. This project seeks to overcome these limitations by designing a football performance analysis system that integrates YOLO with Convolutional Neural Networks (CNNs) and deep learning models. By combining YOLO's real-time detection with CNNs for advanced feature extraction and deep learning for complex pattern recognition, the system aims to analyze player movements, identify technique errors, and provide actionable feedback. This solution will deliver personalized insights for players and strategic data for coaches, fostering improved individual skills and team performance.

1.3 SPECIFIC OBJECTIVES

The primary objective of this project is to create an advanced football performance analysis system by integrating YOLO (You Only Look Once) with Convolutional Neural Networks (CNNs) and deep learning models. This system aims to provide precise, real-time analysis of player movements, shooting accuracy, and optimal positioning. By combining YOLO's object detection capabilities with CNNs for detailed feature extraction and deep learning for recognizing complex patterns, the system will identify technique errors and offer actionable recommendations. The goal is to enhance individual player performance and support coaches in developing strategies, enabling data-driven improvements for both players and teams.

1.4 SIGNIFICANCE AND MOTIVATION FOR OUR PROJECT

The significance of this project lies in its potential to transform football performance analysis by incorporating cutting-edge technologies like Human Action Recognition (HAR), Artificial Intelligence (AI), Deep Learning, and Computer Vision. Traditional methods, which often rely on manual assessments, are limited in precision and scalability. This project addresses these limitations by utilizing advanced tools such as YOLOv8, OpenCV, and Artificial Neural Networks (ANNs) to provide accurate, real-time insights into player movements, shooting accuracy, and positioning. The motivation for this initiative comes from the increasing demand for data-driven approaches in sports, where even small technical improvements can lead to significant gains in performance. By offering personalized feedback to players and helping coaches develop strategies based on comprehensive analysis, this system aims to enhance individual skills and team efficiency, contributing to a more competitive and data-informed approach to modern football.

1.5 EXISTING SYSTEM

Current systems utilizing YOLO (You Only Look Once) for football performance analysis primarily focus on detecting and tracking objects like players, the ball, and field boundaries in real-time. These systems are designed to process video footage captured by standard cameras and rely on YOLO’s high-speed detection capabilities to monitor positions and movements. While effective for basic visual tracking and activity mapping, they lack the integration of advanced technologies such as Convolutional Neural Networks (CNNs), DL algorithms, or additional hardware like sensors and specialized cameras.

In these systems, YOLO is used to analyze game footage, providing insights such as player locations, ball trajectories, and general movement patterns. This data can be used to create simple visualizations like heatmaps or positional charts. However, these systems typically do not extend their functionality to analyze more intricate performance aspects, such as optimal shooting angles, joint movements, or biomechanics, which require deeper data processing capabilities.

The absence of hardware advancements like motion sensors, wearable devices, or high-speed cameras further limits their ability to capture detailed player movements. Consequently, they are unable to measure critical metrics like speed, precision, or body mechanics during gameplay. This lack of integration with additional technologies also means the feedback provided is often generalized and lacks the specificity required for tailored player development.

In summary, while existing YOLO-based systems are efficient for basic object detection and tracking, their reliance on visual data alone and the absence of more advanced AI models and hardware limit their effectiveness. These systems are suitable for generating general performance insights but fall short when it comes to providing in-depth analysis and personalized recommendations for improving player techniques.

1.6 PROPOSED SYSTEM

The proposed system focuses on enhancing football players' performance by analyzing their techniques using advanced technologies such as Human Action Recognition (HAR), Artificial Intelligence (AI), and Deep Learning. The system aims to improve key aspects of gameplay, including shooting accuracy, optimal shooting angles, and positioning, which are critical for maximizing scoring chances and overall efficiency. By leveraging datasets from videos and photos of players, the system evaluates their movements to identify areas for improvement, such as errors in shooting technique, and recommends adjustments. For instance, it can suggest optimal angles for shooting, identify positions with a higher likelihood of scoring, and highlight any technical errors that need correction. This analysis not only helps individual players refine their skills but also aids coaches in designing effective strategies and optimizing player positions during matches.

The system uses advanced tools like OpenCV for measuring movement dynamics and YOLOv8, a cutting-edge computer vision library, to detect and classify features in real time. YOLOv8 is known for its high accuracy in object detection and is particularly useful for analyzing player movements and ball placement during gameplay. The core of the system is powered by Python programming, utilizing a range of open-source libraries for AI and machine learning. Development was carried out using IDEs such as Visual Studio Code and Google Colab, which provide the necessary environment for coding, testing, and model training.

By integrating data-driven insights, the system enables players to receive personalized recommendations aimed at improving their performance. Coaches also benefit from the system by gaining actionable feedback, which helps in optimizing man-marking tactics and other strategic decisions. The data flow begins with the collection of player data from photos and videos, which is processed by the AI algorithms to detect movement patterns and generate feedback. This real-time analysis helps both players and coaches make informed decisions, ultimately leading to improved individual performance and better team strategies.

CHAPTER 2
LITERATURE SURVEY

With the exponential growth of various Machine Learning (ML) and Deep Learning (DL) models, their evaluation and testing are becoming very crucial and essential to predict the accuracies of these models. To understand accuracy, the model must give an average of above 95% for either training dataset or for testing dataset. Main concerns that rise when competing between model accuracies are lack of data and sensitivity.

2.1 ABOUT THE PROJECT

In this project, we leverage cutting-edge deep learning models like **YOLOv8** and **Convolutional Neural Networks (CNNs)** to track and analyze players and ball movement during a game. By using these object detection models, we can accurately identify players on the field, monitor their movements, and track the ball in real-time. This data enables coaches to gain deeper insights into the dynamics of the game, such as how individual players position themselves, how long they maintain possession of the ball, and where the ball moves throughout the match. Such detailed analysis helps coaches understand each player's playing style, strengths, and areas that need improvement, ultimately contributing to more effective training and strategy development. Additionally, teams can use this information to refine their tactics, optimize player performance, and make data-driven decisions during games. The project also aims to advance existing models by integrating **newer sensors**, **improved CNN architectures**, and **updated YOLO versions** to provide more accurate and comprehensive data. This progress opens up new possibilities for improving not only player performance but also overall team strategy, enabling coaches and organizations to identify mistakes, correct tactical issues, and enhance decision-making for better game outcomes.

2.2 LITERATURE REVIEW

Vicente-Martinez et al [1]: This paper presents an innovative approach for detecting and tracking soccer balls using a combination of YOLOv7 and DeepSORT. The authors enhance the YOLOv7 architecture with a focal loss function to improve detection accuracy, achieving a remarkable 95% precision. The study introduces a semi-supervised learning framework, leveraging a dataset of 6331 images, to reduce the reliance on fully labeled data.

The proposed system outperforms previous detection methods, particularly in challenging conditions such as occlusions and fast motion. The results highlight the effectiveness and robustness of this approach for sports analytics.

Y. Yoon et al [2]: This paper introduces a novel system for automatically classifying basketball players and tracking ball movements in game video clips, particularly under challenging conditions such as dynamic camera angles and player overlap. The system leverages YOLO, a real-time object detection framework, combined with Darknet's convolutional neural networks, to identify players and their jersey numbers across video frames and addresses common issues like players moving out of the frame or overlapping in two-dimensional footage.

By leveraging movement history from previous frames, the system improves tracking accuracy despite these challenges. Additionally, the paper employs network science to analyze passing relationships between players, using a multivariate Eigen centrality metric to assess player importance.

R. Romijnders et al [3]: This paper explores the use of Recurrent Neural Networks (RNNs) for predicting the success of three-point shots in basketball, utilizing player and ball tracking data. The study focuses on sequence modeling to classify shot outcomes, showing that RNNs, which rely solely on positional data, outperform traditional machine learning models that incorporate additional features like angle and velocity. Using over 20,000 three-point shot attempts from NBA SportVu data, the RNN model achieves an AUC of 0.843, significantly higher than the AUCs of 0.558 and 0.719 from linear and gradient boosted machine models, respectively.

The paper demonstrates the potential of deep learning, particularly RNNs, to handle noisy and high-velocity motion data in sports analytics. This proposed methodology contributes to advancing predictive modeling in sports by showcasing how RNNs can offer valuable insights into sequential data and trajectory classification.

Wenxin Du et al [4]: This paper discusses about the simulation results show that the correct rate gradually decreases with the increase of the number of wrong actions. This framework develops a dual-channel 3D Convolutional Neural Network (CNN) integrated with a spatial attention mechanism (SA) to enhance action recognition accuracy. The model processes inter-frame difference information alongside grayscale video data, achieving high accuracy in identifying athletes' technical errors.

The proposed methodology primarily focuses on simulation results which demonstrate that the recognition accuracy remains above 87.5% even as the number of errors increases to 400 instances. The method not only improves the ability to objectively assess player performance but also offers robust support for athlete training.

M. Chariar et al [5]: This paper has developed a framework – based algorithms that focuses on applying AI and CV to improve squat performance and prevent injuries, leveraging deep learning techniques for accurate squat classification and correction. The framework proposes a stacked Bidirectional Gated Recurrent Unit (Bi-GRU) model with an attention layer to evaluate squat movements.

The model classifies squats into seven categories and achieves impressive accuracy (94%) in distinguishing correct from incorrect forms. The study uses MediaPipe for pose estimation and compares the Bi-GRU model with other state-of-the-art methods, demonstrating its superior performance and consistency. Additionally, the paper emphasizes personalized correction, tailoring recommendations based on individual body proportions and performance, contributing to a more effective and safe workout analysis system.

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 HARDWARE REQUIREMENTS

- Processor greater than intel core i5.
- RAM Greater than 4GB.
- Hard Disk more than or equal to 500GB

3.2 SOFTWARE REQUIREMENTS

- Windows.
- Python Libraries.
- Yolo
- Google Collab

CHAPTER 4
SYSTEM ARCHITECTURE

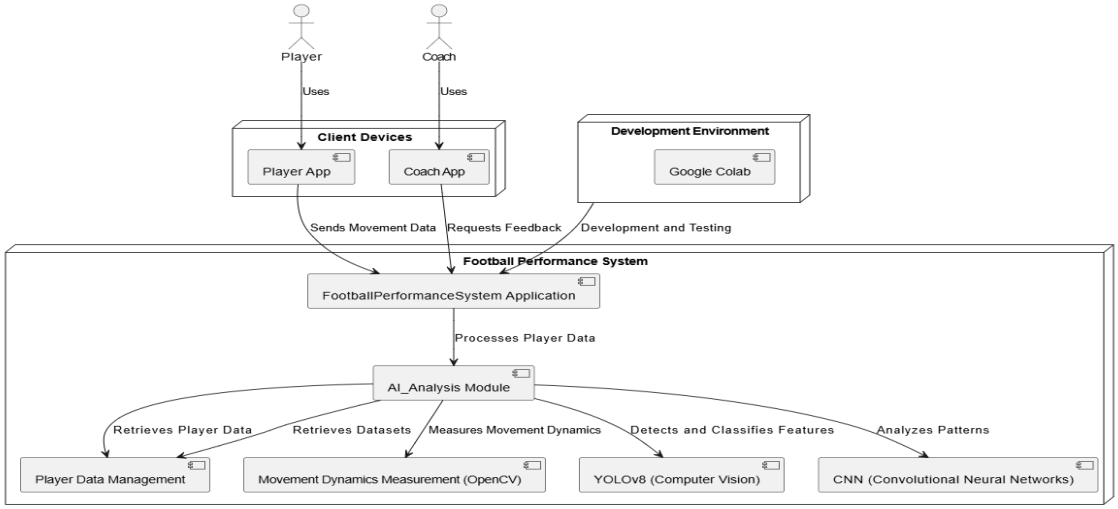


Fig 4.1 : System Architecture

The diagram outlines a workflow for efficiency prediction using synthetic data and an LSTM-RNN model. It begins with the collection of historical data, which is cleaned, normalized, and transformed during the data preparation phase to ensure it is suitable for further processing. Synthetic data generation then creates additional samples to mimic the characteristics of the original dataset. This synthetic data is split into two subsets: synthetic training data, used to train the machine learning model, and synthetic test data, which is utilized to evaluate its performance. The LSTM-RNN predictor, a specialized model designed to handle time-series data, forms the core of this workflow. It uses the synthetic training data to learn patterns and dependencies over time. Once the model is trained, it is validated using synthetic test data to assess its accuracy and generalization capabilities. Upon successful validation, the predictor is deployed for efficiency prediction, where it processes new data to generate reliable and actionable insights.

A feedback loop is incorporated into the system, allowing continuous refinement of the model. New data can be integrated into the synthetic data generation process to further improve the model's predictive capabilities. By leveraging synthetic data and machine learning, this workflow provides a scalable, efficient, and effective solution for predicting efficiency in data- scarce environments.

CHAPTER 5
UML DIAGRAMS

5.1 INTRODUCTION TO UML

Unified Modelling Language (UML) is a standardized modelling tool developed by the **Object Management Group (OMG)** for designing and documenting object-oriented systems. It serves as a universal visual language, helping developers and stakeholders communicate effectively.

UML consists of two key components:

1. **Meta-model**: Defines the structure and rules for creating models.
2. **Notation**: Graphical symbols used to visually represent system components.

UML is not limited to software systems—it is also useful for modelling business processes and other domains. It leverages proven engineering practices, enabling the design of large, complex systems through clear, visual representations.

Goals of UML

The primary goals of UML are:

- Provide a consistent and expressive visual modeling language.
- Enable customization and extension for various needs.
- Maintain independence from specific programming languages and processes.
- Establish a formal foundation for understanding system designs.
- Encourage the growth and adoption of object-oriented tools.
- Support advanced concepts like patterns, frameworks, and components.
- Integrate industry best practices to improve design quality.

Importance of UML

UML simplifies the process of designing object-oriented systems by offering a visual representation of system components and interactions. It helps teams identify potential issues early, ensures consistent understanding, and enhances collaboration throughout development. Its graphical approach makes it a vital tool for building robust, scalable systems.

5.2 UML DIAGRAMS

5.2.1 USE CASE DIAGRAM:

A **use case diagram** in **Unified Modelling Language (UML)** is a type of behavioural diagram that originates from use-case analysis. It provides a visual summary of a system's functionality by illustrating the interactions between the system's actors, their objectives (depicted as use cases), and the relationships among these use cases.

The primary purpose of a use case diagram is to identify which system functions are associated with specific actors. It highlights the roles of each actor and how they interact with the system, offering a clear picture of the system's functionality and user interactions.

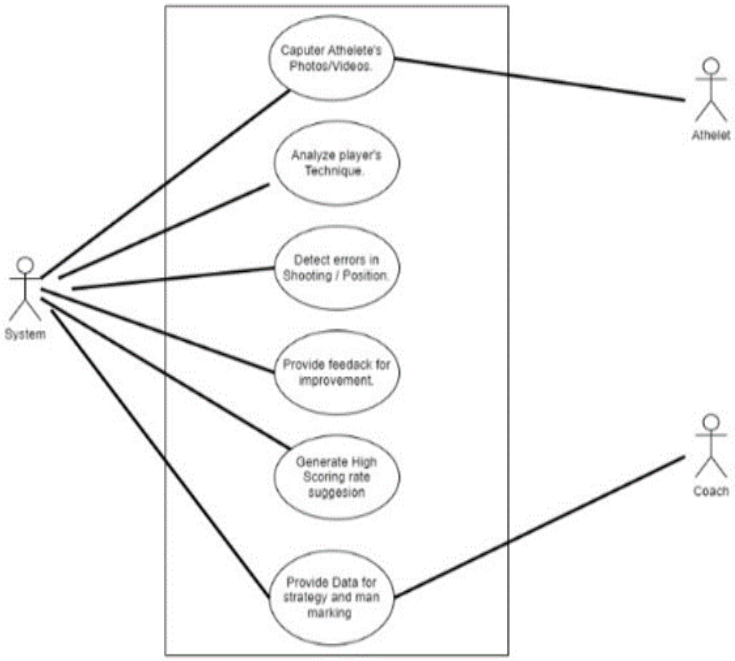


Fig 5.1: Use Case Diagram

5.2.2 ACTIVITY DIAGRAM

The activity diagram captures the flow of processes within a system. Similar to a state diagram, it includes elements such as activities, actions, transitions, initial and final states, and conditions (known as guard conditions) that influence the flow. This diagram provides a visual representation of how tasks are carried out and how different states connect within a process.

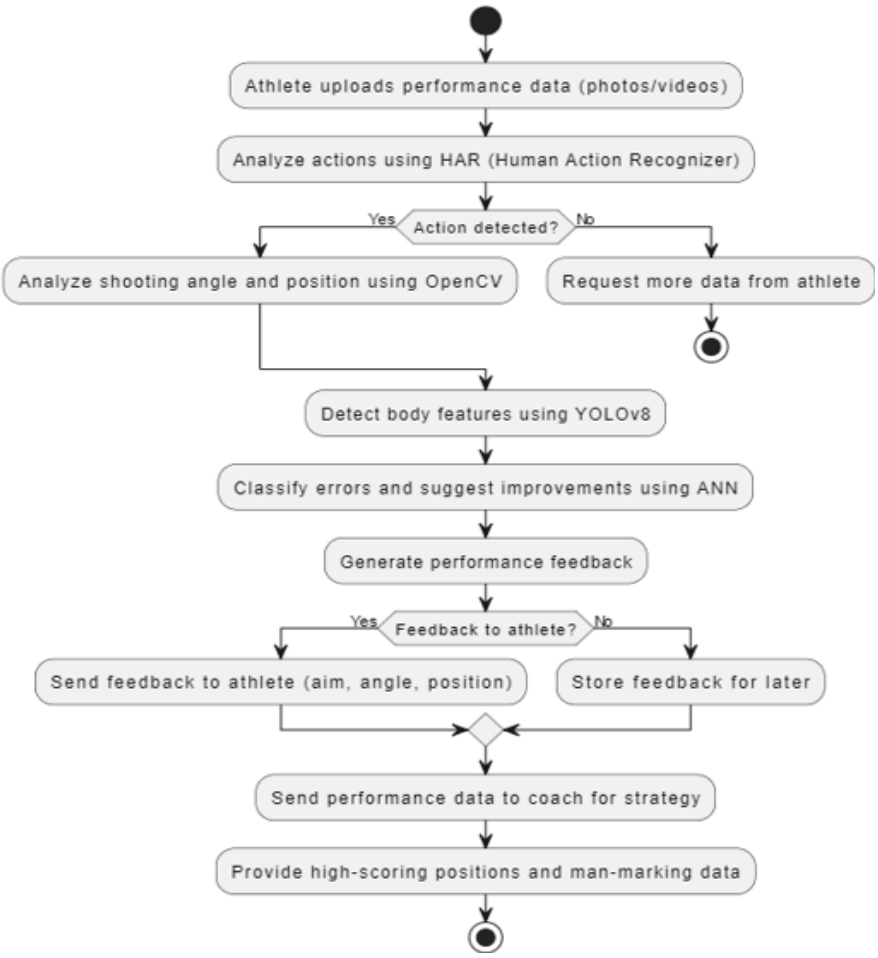


Fig 5.2: Activity Diagram

5.2.3 SEQUENCE DIAGRAM

A sequence diagram illustrates how various objects in a system interact with one another over time. The key feature of a sequence diagram is its time-ordered nature, which means it visually represents the exact order of interactions step by step. Objects in the diagram communicate by exchanging "messages," showing the flow of information or control between them.

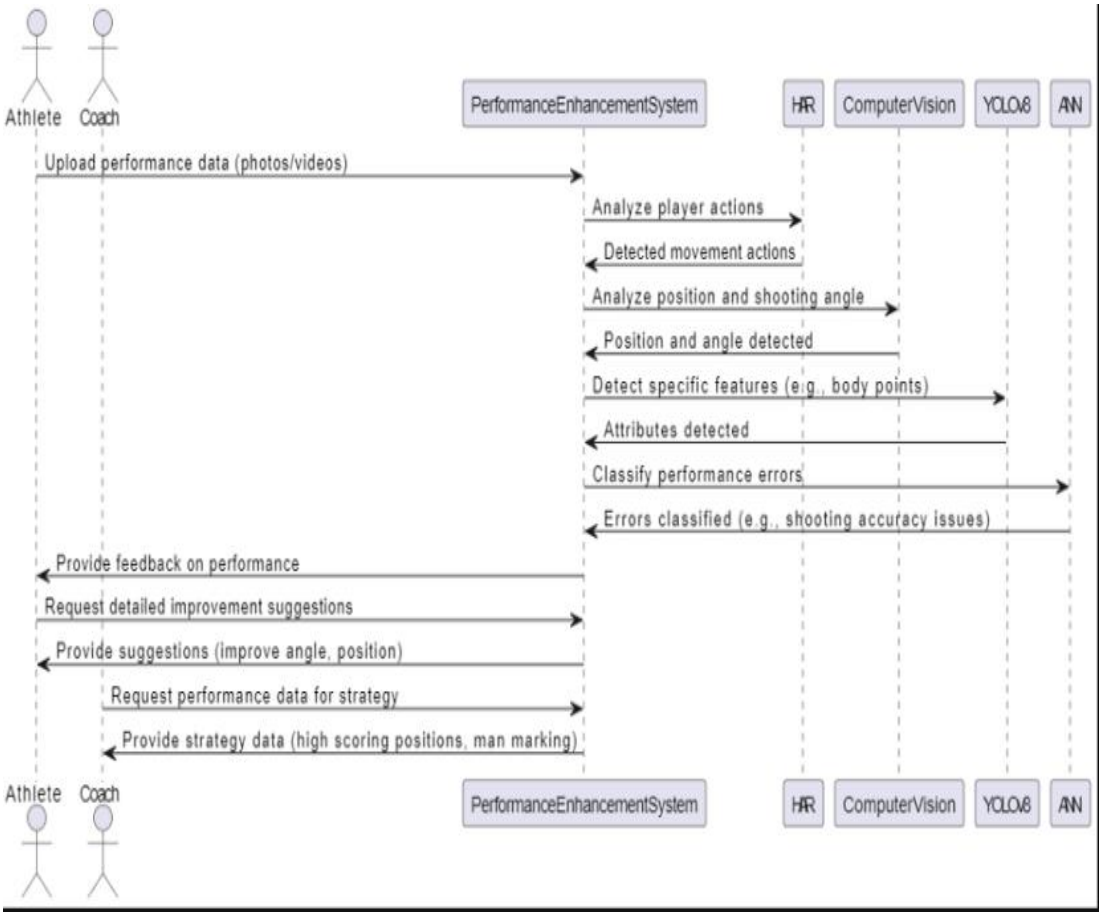


Fig 5.3: Sequence Diagram

5.2.4 STATE CHART DIAGRAM

State chart diagrams, also known as state machine diagrams, are essential tools for visualizing the dynamic behaviour of an object and how it responds to various events. These diagrams effectively illustrate the transitions an object undergoes throughout its lifecycle, providing a structured representation of its state changes triggered by internal or external factors.

The significance of state chart diagrams can be summarized as follows:

- They model the lifecycle of an object, detailing its progression through various states.
- They explain state transitions by highlighting the events that trigger changes and how the object responds to these stimuli.
- They capture and represent complex behaviours, including entry and exit actions, actions performed within a state, and the conditions governing state transitions.

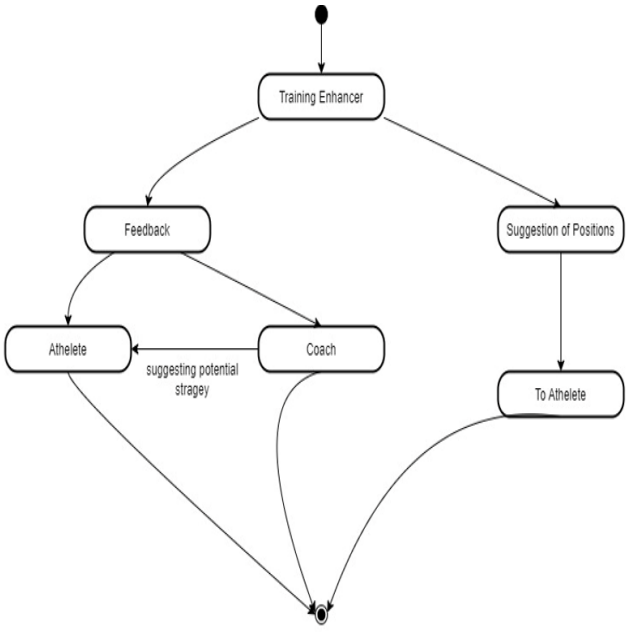


Fig 5.4: State Chart Diagram

5.2.5 OBJECT DIAGRAM

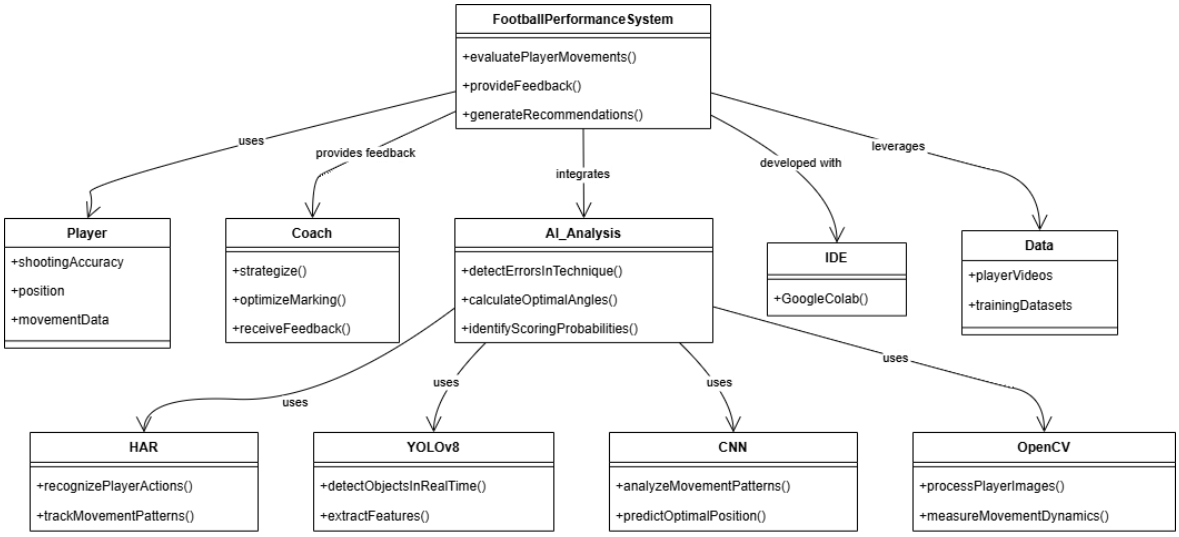


Fig 5.5: Object diagram

An Object Diagram in UML can be thought of as a snapshot of the instances within a system and the relationships between them at a specific moment in time. This type of diagram is a key component of UML, offering a clear and concise visualization of how objects interact and are connected. By focusing on specific instances of classes and their associations, object diagrams help to communicate and understand the structure and behavior of a system more effectively.

In essence, an object diagram provides a detailed view of the system's structure at a particular point, serving as a tool to illustrate real-world examples of data structures. While their use is somewhat limited, object diagrams are particularly valuable during the analysis phase of a project. Typically, a class diagram is first created to define the system’s overall structure, and then object diagrams are developed to validate the class diagram through concrete examples, ensuring its accuracy and completeness.

5.2.6 DEPLOYMENT DIAGRAM

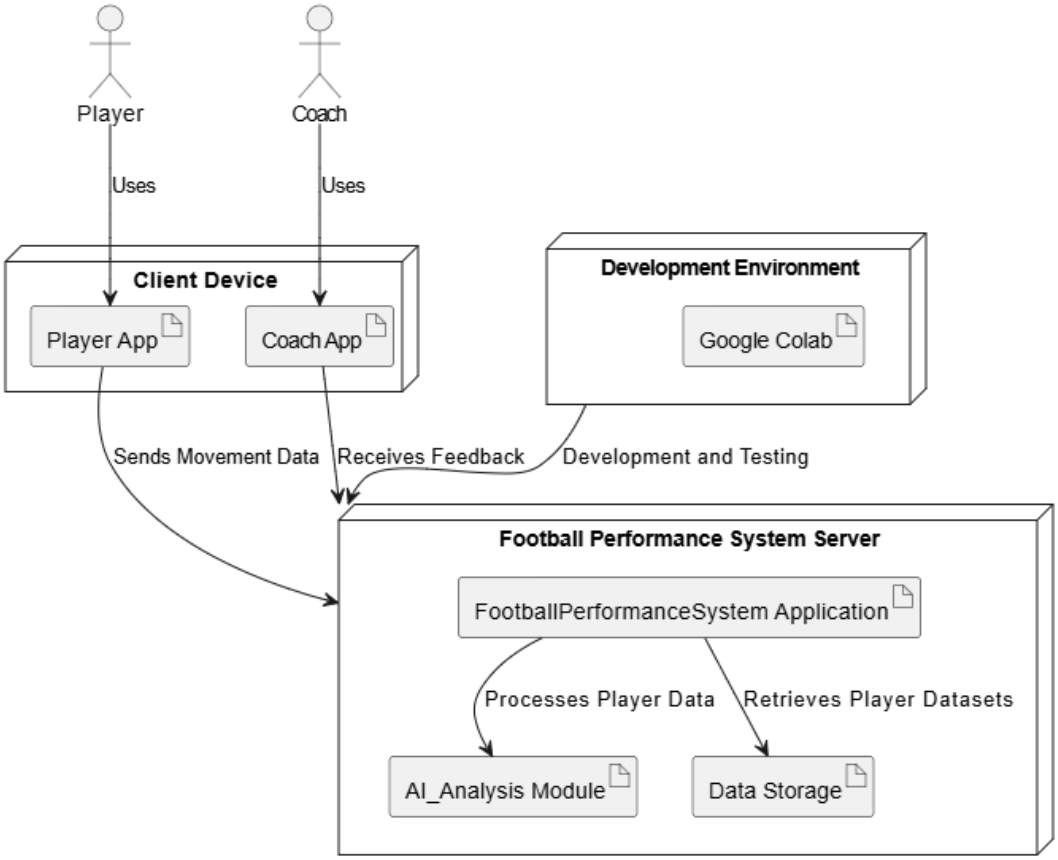


Fig 5.6: Deployment diagram

The deployment diagram provides a clear representation of how the application's runtime elements are configured. It becomes particularly valuable during the final stages of development when the system is ready for deployment, offering insights into the arrangement of components in the production environment.

5.2.7 COMPONENT DIAGRAM

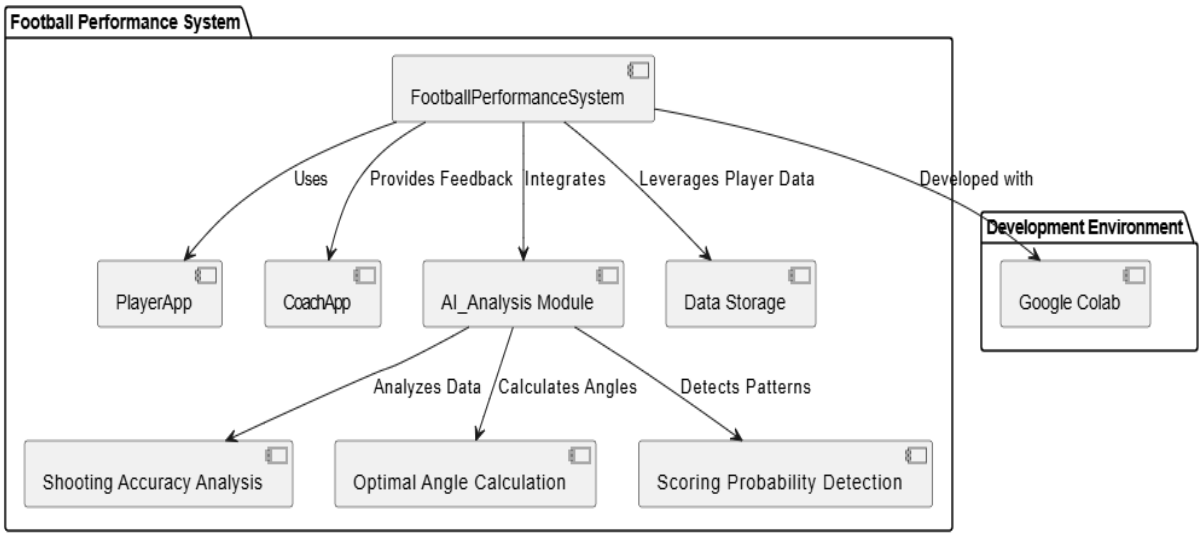


Fig 5.7: Component diagram

A component diagram serves as a critical tool for depicting the foundational structure of a system, offering a clear visualization of the various components that make up the system and the interactions between them. It highlights the key building blocks, their functions, and the relationships that enable them to work together as part of the system's architecture. Typically, this diagram is created after the system has progressed through the design, development, or implementation phases. It provides a snapshot of the system's composition, focusing on the essential elements and their dependencies. By offering a high-level view, component diagrams help developers, architects, and stakeholders understand how the components are organized and connected, ensuring a shared understanding of the system's architecture and facilitating efficient communication and planning.

5.2.8 COLLABORATION DIAGRAM

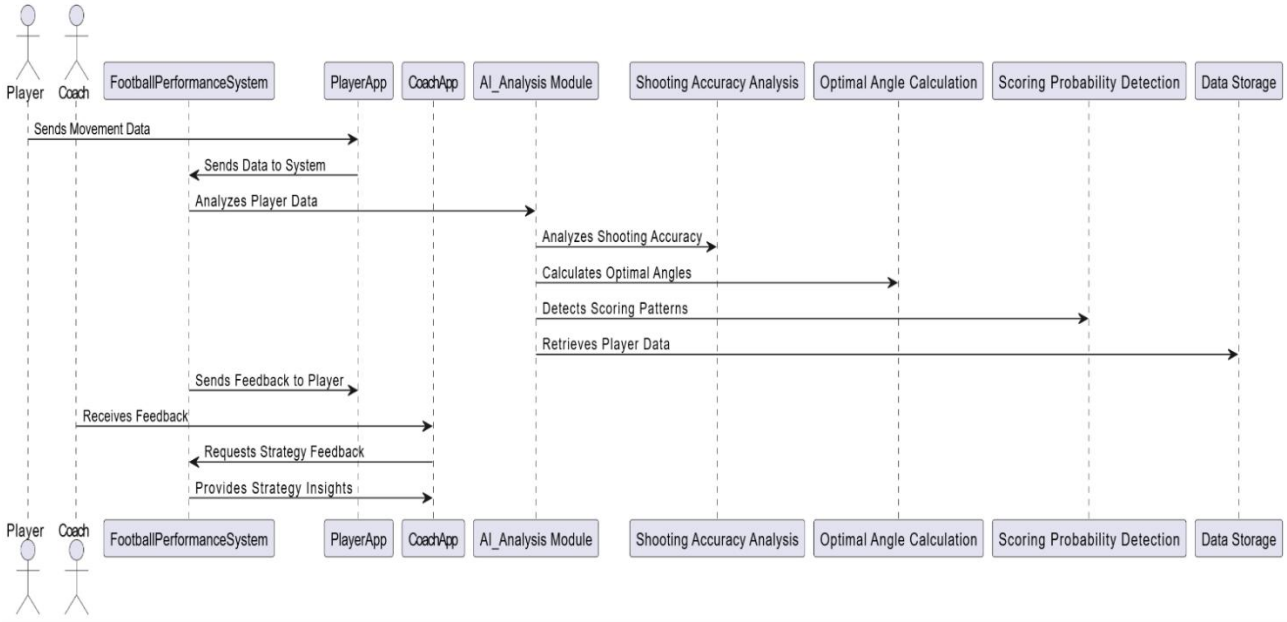


Fig 5.8: Collaboration diagram

Collaboration diagrams illustrate how objects interact to carry out the behavior of a use case or its part. Alongside sequence diagrams, they help designers define the roles of objects in a use case flow, serving as a key source for determining class responsibilities and interfaces.

These diagrams focus on the structural aspect of interactions, showing how lifelines are connected. The syntax resembles that of sequence diagrams, with the key difference being that lifelines do not have tails. Messages are numbered to indicate their sequence. However, collaboration diagrams are semantically less detailed than sequence diagrams.

5.3 ARCHITECTURE DIAGRAM

An architectural model in software is a structured and detailed diagram that adheres to established standards, designed to represent the key trade-offs in the system's design and structure. Software architects create these models to effectively communicate design choices and solicit feedback from colleagues and stakeholders. The architectural model serves as a representation of a specific perspective within the software architecture.

Essentially, the purpose of creating an architectural model is to communicate a particular message and gather valuable input from others. The diagram aims to answer a specific question, allowing others to (a) assess whether they agree with the interpretation and (b) use the insights to inform and shape their own work.

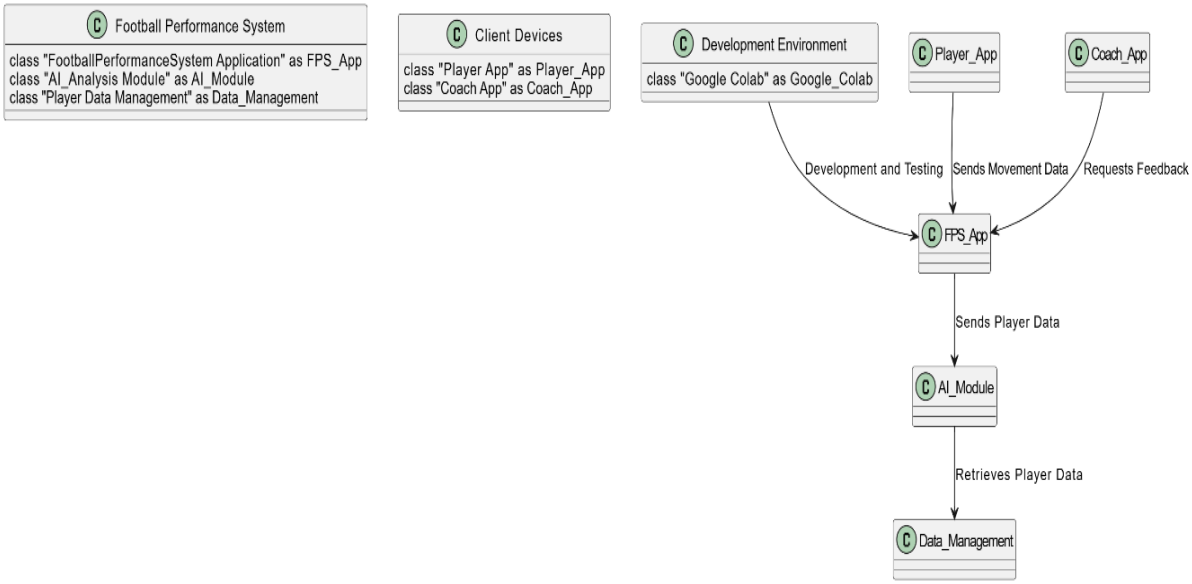


Fig 5.9: Architecture Diagram

5.4 CLASS DIAGRAM

The class diagram refines the use case diagram and provides a more detailed design of the system. It organizes the actors from the use case diagram into a set of interconnected classes. The relationships between these classes can be either an "is-a" or "has-a" type. Each class is responsible for certain functionalities, referred to as "methods," which define its behavior. Additionally, each class may have specific "attributes" that uniquely distinguish it from others, helping to define its characteristics.

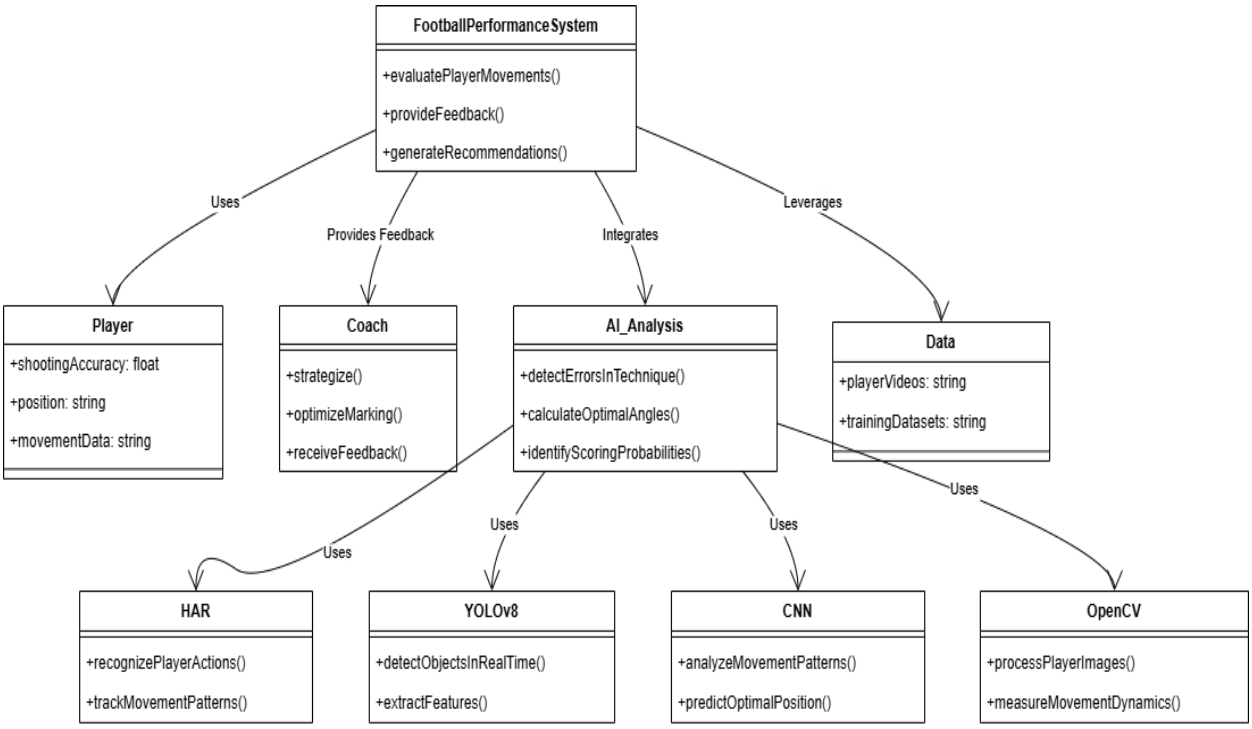


Fig 5.10: Class Diagram

5.5 ALGORITHM

Step 1: Initialization

Data Input: Takes the video frames, images of athlete while training

Step 2: Enter Loop

Continuous Loop: Begin a loop that will run indefinitely until a stopping condition is met.

Step 3: Check Errors

Identifying errors in players while

playing:

If the athlete data has errors:

Then it identifies the errors with the help of yoloV8 and CNN modules.

Step 4: Player Evaluation

Player Check:

If the player has errors:

Apply CNN Models: Utilize various CNN models, such as YoloV8, OpenCV to analyze the data.

Ensemble Learning Approach: Implement an ensemble learning strategy to combine multiple models for improved performance and accuracy.

If the player has no errors:

Skip to Step 6: Bypass the modeling step and proceed to the conclusion.

Step 5: Display Results

Display Athlete Data: Present the Athlete data for review.

Step 6: User Interaction

Gather User Input:

For each result generated, read user input to specify:

- Attributes
- Data characteristics
- Useful CNN models that can be applied.

Step 7: Conclusion

End Process: Exit the loop and stop the algorithm once all necessary steps have been completed and user input has been processed.

This structured approach ensures that the algorithm effectively generates player's data and the coach can later check and interact with the player accordingly throughout the process.

Data: Videos and images.
Result: Enhancer for athlete to improve their gameplay.
initializations;
STEP I:
while *TRUE* **do**
  STEP II:
  if (
    Athlete has errors
) then
    Rectifies and improves the shooting angle;
  end
  STEP III:
  if (
    Athletes has no errors
) then
    Provides strategies and intimates it to the coach;
  else
    goto "STEP VI";
  end
  STEP IV: Display the Athlete's Performance
  STEP V:
  for *Result in Result* **do**
    read user input;
    get Images, Videos, Useful ML Models, Shooting angles, CNN;
  end
end
STEP VI: STOP

Algorithm 1: How proposed model works.

Fig 5.11: Algorithm

CHAPTER 6
CODE IMPLEMENTATION

6.1 CODE SAMPLE

```
import os
os.environ["ONNXRUNTIME_EXECUTION_PROVIDERS"]=
"[CUDAExecutionProvider]"

#ball, player, goalkeeper and referee detection

from inference import get_model
from google.colab import userdata

ROBOFLOW_API_KEY = userdata.get('ROBOFLOW_API_KEY')
PLAYER_DETECTION_MODEL_ID = "football-players-detection-3zvbc/11"
PLAYER_DETECTION_MODEL=
get_model(model_id=PLAYER_DETECTION_MODEL_ID,
api_key=ROBOFLOW_API_KEY)

import supervision as sv

SOURCE_VIDEO_PATH = "/content/121364_0.mp4"

box_annotator = sv.BoxAnnotator(
    color=sv.ColorPalette.from_hex(['#FF8C00', '#00BFFF', '#FF1493', '#FFD700']),
    thickness=2)
label_annotator = sv.LabelAnnotator(
    color=sv.ColorPalette.from_hex(['#FF8C00', '#00BFFF', '#FF1493', '#FFD700']),
    text_color=sv.Color.from_hex('#000000'))

frame_generator = sv.get_video_frames_generator(SOURCE_VIDEO_PATH)
frame = next(frame_generator)

result = PLAYER_DETECTION_MODEL.infer(frame, confidence=0.3)[0]
detections = sv.Detections.from_inference(result)

labels = [
    f"{class_name} {confidence:.2f}"
```

```
    for class_name, confidence
    in zip(detections['class_name'], detections.confidence)]

annotated_frame = frame.copy()
annotated_frame = box_annotator.annotate(
    scene=annotated_frame,
    detections=detections)
annotated_frame = label_annotator.annotate(
    scene=annotated_frame,
    detections=detections,
    labels=labels)

sv.plot_image(annotated_frame)

#video game style visualization

import supervision as sv

SOURCE_VIDEO_PATH = "/content/121364_0.mp4"
BALL_ID = 0

ellipse_annotator = sv.EllipseAnnotator(
    color=sv.ColorPalette.from_hex(['#00BFFF', '#FF1493', '#FFD700']),
    thickness=2
)
triangle_annotator = sv.TriangleAnnotator(
    color=sv.Color.from_hex('#FFD700'),
    base=25,
    height=21,
    outline_thickness=1
)

frame_generator = sv.get_video_frames_generator(SOURCE_VIDEO_PATH)
frame = next(frame_generator)

result = PLAYER_DETECTION_MODEL.infer(frame, confidence=0.3)[0]
detections = sv.Detections.from_inference(result)

ball_detections = detections[detections.class_id == BALL_ID]
ball_detections.xyxy = sv.pad_boxes(xyxy=ball_detections.xyxy, px=10)
```

```
all_detections = detections[detections.class_id != BALL_ID]
all_detections = all_detections.with_nms(threshold=0.5, class_agnostic=True)
all_detections.class_id -= 1

annotated_frame = frame.copy()
annotated_frame = ellipse_annotator.annotate(
   scene=annotated_frame,
   detections=all_detections)
annotated_frame = triangle_annotator.annotate(
   scene=annotated_frame,
   detections=ball_detections)

sv.plot_image(annotated_frame)

#player tracking

import supervision as sv

SOURCE_VIDEO_PATH = "/content/121364_0.mp4"
BALL_ID = 0

ellipse_annotator = sv.EllipseAnnotator(
   color=sv.ColorPalette.from_hex(['#00BFFF', '#FF1493', '#FFD700']),
   thickness=2)
label_annotator = sv.LabelAnnotator(
   color=sv.ColorPalette.from_hex(['#00BFFF', '#FF1493', '#FFD700']),
   text_color=sv.Color.from_hex('#000000'),
   text_position=sv.Position.BOTTOM_CENTER)
triangle_annotator = sv.TriangleAnnotator(
   color=sv.Color.from_hex('#FFD700'),
   base=25,
   height=21,
   outline_thickness=1)

tracker = sv.ByteTrack()
tracker.reset()

frame_generator = sv.get_video_frames_generator(SOURCE_VIDEO_PATH)
frame = next(frame_generator)
```

```
result = PLAYER_DETECTION_MODEL.infer(frame, confidence=0.3)[0]
detections = sv.Detections.from_inference(result)

ball_detections = detections[detections.class_id == BALL_ID]
ball_detections.xyxy = sv.pad_boxes(xyxy=ball_detections.xyxy, px=10)

all_detections = detections[detections.class_id != BALL_ID]
all_detections = all_detections.with_nms(threshold=0.5, class_agnostic=True)
all_detections.class_id -= 1
all_detections = tracker.update_with_detections(detections=all_detections)

labels = [
    f"#{tracker_id}"
    for tracker_id
    in all_detections.tracker_id]

annotated_frame = frame.copy()
annotated_frame = ellipse_annotator.annotate(
    scene=annotated_frame,
    detections=all_detections)
annotated_frame = label_annotator.annotate(
    scene=annotated_frame,
    detections=all_detections,
    labels=labels)
annotated_frame = triangle_annotator.annotate(
    scene=annotated_frame,
    detections=ball_detections)

sv.plot_image(annotated_frame)

#split players into teams

# Before training our player clustering model, we need to gather training data. To do this, we'll sample one frame per second, detect players within those frames, and then crop them out.

from tqdm import tqdm

SOURCE_VIDEO_PATH = "/content/121364_0.mp4"
PLAYER_ID = 2
```

```
STRIDE = 30

frame_generator = sv.get_video_frames_generator(
   source_path=SOURCE_VIDEO_PATH, stride=STRIDE)

crops = []
for frame in tqdm(frame_generator, desc='collecting crops'):
   result = PLAYER_DETECTION_MODEL.infer(frame, confidence=0.3)[0]
   detections = sv.Detections.from_inference(result)
   detections = detections.with_nms(threshold=0.5, class_agnostic=True)
   detections = detections[detections.class_id == PLAYER_ID]
   players_crops = [sv.crop_image(frame, xyxy) for xyxy in detections.xyxy]
   crops += players_crops
sv.plot_images_grid(crops[:100], grid_size=(10, 10))

#Note: Next, we'll run SigLIP to calculate embeddings for each of the crops.

import torch
from transformers import AutoProcessor, SiglipVisionModel

SIGLIP_MODEL_PATH = 'google/siglip-base-patch16-224'

DEVICE = 'cuda' if torch.cuda.is_available() else 'cpu'
EMBEDDINGS_MODEL=
SiglipVisionModel.from_pretrained(SIGLIP_MODEL_PATH).to(DEVICE)
EMBEDDINGS_PROCESSOR=
AutoProcessor.from_pretrained(SIGLIP_MODEL_PATH)

import numpy as np
from more_itertools import chunked

BATCH_SIZE = 32

crops = [sv.cv2_to_pillow(crop) for crop in crops]
batches = chunked(crops, BATCH_SIZE)
data = []
with torch.no_grad():
   for batch in tqdm(batches, desc='embedding extraction'):

inputs=EMBEDDINGS_PROCESSOR(images=batch,return_tensors="pt").to(DEVICE
```

```
)
        outputs = EMBEDDINGS_MODEL(**inputs)
        embeddings = torch.mean(outputs.last_hidden_state, dim=1).cpu().numpy()
        data.append(embeddings)

data = np.concatenate(data)

# Using UMAP, we project our embeddings from (N, 768) to (N, 3) and then perform a two-cluster division using KMeans.

import umap
from sklearn.cluster import KMeans

REDUCER = umap.UMAP(n_components=3)
CLUSTERING_MODEL = KMeans(n_clusters=2)
projections = REDUCER.fit_transform(data)
clusters = CLUSTERING_MODEL.fit_predict(projections)

# Here's an interactive visualization of our results. Click on a dot to display its associated crop.

import plotly.graph_objects as go
import numpy as np
from typing import Dict, List
from IPython.core.display import display, HTML
from PIL import Image
import base64
from io import BytesIO

def pil_image_to_data_uri(image: Image.Image) -> str:
    buffered = BytesIO()
    image.save(buffered, format="PNG")
    img_str = base64.b64encode(buffered.getvalue()).decode("utf-8")
    return f"{img_str}"

def display_projections(
    labels: np.ndarray,
    projections: np.ndarray,
    images: List[Image.Image],
    show_legend: bool = False,
```

```
    show_markers_with_text: bool = True
) -> None:
    image_data_uris = {f"image_{i}": pil_image_to_data_uri(image) for i, image in enumerate(images)}
    image_ids = np.array([f"image_{i}" for i in range(len(images))])

    unique_labels = np.unique(labels)
    traces = []
    for unique_label in unique_labels:
        mask = labels == unique_label
        customdata_masked = image_ids[mask]
        trace = go.Scatter3d(
            x=projections[mask][:, 0],
            y=projections[mask][:, 1],
            z=projections[mask][:, 2],
            mode='markers+text' if show_markers_with_text else 'markers',
            text=labels[mask],
            customdata=customdata_masked,
            name=str(unique_label),
            marker=dict(size=8),
            hovertemplate="<b>class:%{text}</b><br>imageID: %{customdata}<extra></extra>"
        )
        traces.append(trace)

    fig = go.Figure(data=traces)
    fig.update_layout(
        scene=dict(xaxis_title='X', yaxis_title='Y', zaxis_title='Z'),
        width=1000,
        height=1000,
        showlegend=show_legend
    )

    plotly_div = fig.to_html(full_html=False, include_plotlyjs=False, div_id="scatter-plot-3d")

    javascript_code = f"""
    <script>
        function displayImage(imageId) {{
            var imageElement = document.getElementById('image-display');
```

```
        var placeholderText = document.getElementById('placeholder-text');
        var imageDataURIs = {image_data_uris};
        imageElement.src = imageDataURIs[imageId];
        imageElement.style.display = 'block';
        placeholderText.style.display = 'none';
    }}

    var chartElement = document.getElementById('scatter-plot-3d');

    chartElement.on('plotly_click', function(data) {{
        var customdata = data.points[0].customdata;
        displayImage(customdata);
    }});
</script>
"""

html_template = f"""
<!DOCTYPE html>
<html>
    <head>
        <script src="https://cdn.plot.ly/plotly-latest.min.js"></script>
        <style>
            #image-container {{
                position: fixed;
                top: 0;
                left: 0;
                width: 200px;
                height: 200px;
                padding: 5px;
                border: 1px solid #ccc;
                background-color: white;
                z-index: 1000;
                box-sizing: border-box;
                display: flex;
                align-items: center;
                justify-content: center;
                text-align: center;
            }}
            #image-display {{
                width: 100%;
```

```
            height: 100%;
            object-fit: contain;
        }}
      </style>
    </head>
    <body>
      {plotly_div}
      <div id="image-container">
        <img id="image-display" src="" alt="Selected image" style="display: none;" />
        <p id="placeholder-text">Click on a data entry to display an image</p>
      </div>
      {javascript_code}
    </body>
  </html>
  """

display(HTML(html_template))

display_projections(clusters, projections, crops)

import supervision as sv

SOURCE_VIDEO_PATH = "/content/121364_0.mp4"
BALL_ID = 0
GOALKEEPER_ID = 1
PLAYER_ID = 2
REFEREE_ID = 3

ellipse_annotator = sv.EllipseAnnotator(
  color=sv.ColorPalette.from_hex(['#00BFFF', '#FF1493', '#FFD700']),
  thickness=2
)
label_annotator = sv.LabelAnnotator(
  color=sv.ColorPalette.from_hex(['#00BFFF', '#FF1493', '#FFD700']),
  text_color=sv.Color.from_hex('#000000'),
  text_position=sv.Position.BOTTOM_CENTER
)
triangle_annotator = sv.TriangleAnnotator(
  color=sv.Color.from_hex('#FFD700'),
  base=25,
```

```
    height=21,
    outline_thickness=1
)

tracker = sv.ByteTrack()
tracker.reset()

frame_generator = sv.get_video_frames_generator(SOURCE_VIDEO_PATH)
frame = next(frame_generator)

result = PLAYER_DETECTION_MODEL.infer(frame, confidence=0.3)[0]
detections = sv.Detections.from_inference(result)

ball_detections = detections[detections.class_id == BALL_ID]
ball_detections.xyxy = sv.pad_boxes(xyxy=ball_detections.xyxy, px=10)

all_detections = detections[detections.class_id != BALL_ID]
all_detections = all_detections.with_nms(threshold=0.5, class_agnostic=True)
all_detections = tracker.update_with_detections(detections=all_detections)

goalkeepers_detections = all_detections[all_detections.class_id == GOALKEEPER_ID]
players_detections = all_detections[all_detections.class_id == PLAYER_ID]
referees_detections = all_detections[all_detections.class_id == REFEREE_ID]

players_crops = [sv.crop_image(frame, xyxy) for xyxy in players_detections.xyxy]
players_detections.class_id = team_classifier.predict(players_crops)

goalkeepers_detections.class_id = resolve_goalkeepers_team_id(
    players_detections, goalkeepers_detections)

referees_detections.class_id -= 1

all_detections = sv.Detections.merge([
    players_detections, goalkeepers_detections, referees_detections])

labels = [
    f"#{tracker_id}"
    for tracker_id
    in all_detections.tracker_id
]
```

```
all_detections.class_id = all_detections.class_id.astype(int)

annotated_frame = frame.copy()
annotated_frame = ellipse_annotator.annotate(
    scene=annotated_frame,
    detections=all_detections)
annotated_frame = label_annotator.annotate(
    scene=annotated_frame,
    detections=all_detections,
    labels=labels)
annotated_frame = triangle_annotator.annotate(
    scene=annotated_frame,
    detections=ball_detections)

sv.plot_image(annotated_frame)

#Draws a Voronoi diagram on a soccer pitch representing the control areas of two
teams with smooth color transitions.

import supervision as sv
from sports.annotators.soccer import (
    draw_pitch,
    draw_points_on_pitch,
    draw_pitch_voronoi_diagram
)

SOURCE_VIDEO_PATH = "/content/121364_0.mp4"
BALL_ID = 0
GOALKEEPER_ID = 1
PLAYER_ID = 2
REFEREE_ID = 3

ellipse_annotator = sv.EllipseAnnotator(
    color=sv.ColorPalette.from_hex(['#00BFFF', '#FF1493', '#FFD700']),
    thickness=2
)
label_annotator = sv.LabelAnnotator(
    color=sv.ColorPalette.from_hex(['#00BFFF', '#FF1493', '#FFD700']),
    text_color=sv.Color.from_hex('#000000'),
    text_position=sv.Position.BOTTOM_CENTER
```

```
)
triangle_annotator = sv.TriangleAnnotator(
    color=sv.Color.from_hex('#FFD700'),
    base=20, height=17
)

tracker = sv.ByteTrack()
tracker.reset()

frame_generator = sv.get_video_frames_generator(SOURCE_VIDEO_PATH)
frame = next(frame_generator)

# ball, goalkeeper, player, referee detection

result = PLAYER_DETECTION_MODEL.infer(frame, confidence=0.3)[0]
detections = sv.Detections.from_inference(result)

ball_detections = detections[detections.class_id == BALL_ID]
ball_detections.xyxy = sv.pad_boxes(xyxy=ball_detections.xyxy, px=10)

all_detections = detections[detections.class_id != BALL_ID]
all_detections = all_detections.with_nms(threshold=0.5, class_agnostic=True)
all_detections = tracker.update_with_detections(detections=all_detections)

goalkeepers_detections = all_detections[all_detections.class_id == GOALKEEPER_ID]
players_detections = all_detections[all_detections.class_id == PLAYER_ID]
referees_detections = all_detections[all_detections.class_id == REFEREE_ID]

# team assignment

players_crops = [sv.crop_image(frame, xyxy) for xyxy in players_detections.xyxy]
players_detections.class_id = team_classifier.predict(players_crops)

goalkeepers_detections.class_id = resolve_goalkeepers_team_id(
    players_detections, goalkeepers_detections)

referees_detections.class_id -= 1

all_detections = sv.Detections.merge([
    players_detections, goalkeepers_detections, referees_detections])
```

```
# frame visualization

labels = [
    f"#{tracker_id}"
    for tracker_id
    in all_detections.tracker_id
]

all_detections.class_id = all_detections.class_id.astype(int)

annotated_frame = frame.copy()
annotated_frame = ellipse_annotator.annotate(
    scene=annotated_frame,
    detections=all_detections)
annotated_frame = label_annotator.annotate(
    scene=annotated_frame,
    detections=all_detections,
    labels=labels)
annotated_frame = triangle_annotator.annotate(
    scene=annotated_frame,
    detections=ball_detections)

sv.plot_image(annotated_frame)

players_detections = sv.Detections.merge([
    players_detections, goalkeepers_detections
])

# detect pitch key points

result = FIELD_DETECTION_MODEL.infer(frame, confidence=0.3)[0]
key_points = sv.KeyPoints.from_inference(result)

# project ball, players and referies on pitch

filter = key_points.confidence[0] > 0.5
frame_reference_points = key_points.xy[0][filter]
pitch_reference_points = np.array(CONFIG.vertices)[filter]

transformer = ViewTransformer(
```

```
    source=frame_reference_points,
    target=pitch_reference_points )

frame_ball_xy                                                    =
ball_detections.get_anchors_coordinates(sv.Position.BOTTOM_CENTER)
pitch_ball_xy = transformer.transform_points(points=frame_ball_xy)

players_xy                                                       =
players_detections.get_anchors_coordinates(sv.Position.BOTTOM_CENTER)
pitch_players_xy = transformer.transform_points(points=players_xy)

referees_xy                                                      =
referees_detections.get_anchors_coordinates(sv.Position.BOTTOM_CENTER)
pitch_referees_xy = transformer.transform_points(points=referees_xy)

# visualize video game-style radar view

annotated_frame = draw_pitch(CONFIG)
annotated_frame = draw_points_on_pitch(
    config=CONFIG,
    xy=pitch_ball_xy,
    face_color=sv.Color.WHITE,
    edge_color=sv.Color.BLACK,
    radius=10,
    pitch=annotated_frame)
annotated_frame = draw_points_on_pitch(
    config=CONFIG,
    xy=pitch_players_xy[players_detections.class_id == 0],
    face_color=sv.Color.from_hex('00BFFF'),
    edge_color=sv.Color.BLACK,
    radius=16,
    pitch=annotated_frame)
annotated_frame = draw_points_on_pitch(
    config=CONFIG,
    xy=pitch_players_xy[players_detections.class_id == 1],
    face_color=sv.Color.from_hex('FF1493'),
    edge_color=sv.Color.BLACK,
    radius=16,
    pitch=annotated_frame)
annotated_frame = draw_points_on_pitch(
```

```
    config=CONFIG,
    xy=pitch_referees_xy,
    face_color=sv.Color.from_hex('FFD700'),
    edge_color=sv.Color.BLACK,
    radius=16,
    pitch=annotated_frame)

sv.plot_image(annotated_frame)

# visualize voronoi diagram

annotated_frame = draw_pitch(CONFIG)
annotated_frame = draw_pitch_voronoi_diagram(
    config=CONFIG,
    team_1_xy=pitch_players_xy[players_detections.class_id == 0],
    team_2_xy=pitch_players_xy[players_detections.class_id == 1],
    team_1_color=sv.Color.from_hex('00BFFF'),
    team_2_color=sv.Color.from_hex('FF1493'),
    pitch=annotated_frame)

sv.plot_image(annotated_frame)

# visualize voronoi diagram with blend

annotated_frame = draw_pitch(
    config=CONFIG,
    background_color=sv.Color.WHITE,
    line_color=sv.Color.BLACK
)
annotated_frame = draw_pitch_voronoi_diagram_2(
    config=CONFIG,
    team_1_xy=pitch_players_xy[players_detections.class_id == 0],
    team_2_xy=pitch_players_xy[players_detections.class_id == 1],
    team_1_color=sv.Color.from_hex('00BFFF'),
    team_2_color=sv.Color.from_hex('FF1493'),
    pitch=annotated_frame)
annotated_frame = draw_points_on_pitch(
    config=CONFIG,
    xy=pitch_ball_xy,
    face_color=sv.Color.WHITE,
```

```
    edge_color=sv.Color.WHITE,
    radius=8,
    thickness=1,
    pitch=annotated_frame)
annotated_frame = draw_points_on_pitch(
    config=CONFIG,
    xy=pitch_players_xy[players_detections.class_id == 0],
    face_color=sv.Color.from_hex('00BFFF'),
    edge_color=sv.Color.WHITE,
    radius=16,
    thickness=1,
    pitch=annotated_frame)
annotated_frame = draw_points_on_pitch(
    config=CONFIG,
    xy=pitch_players_xy[players_detections.class_id == 1],
    face_color=sv.Color.from_hex('FF1493'),
    edge_color=sv.Color.WHITE,
    radius=16,
    thickness=1,
    pitch=annotated_frame)

sv.plot_image(annotated_frame)

#ball tracking:

from collections import deque
import supervision as sv
from sports.annotators.soccer import draw_pitch, draw_points_on_pitch

SOURCE_VIDEO_PATH = "/content/121364_0.mp4"
BALL_ID = 0
MAXLEN = 5

video_info = sv.VideoInfo.from_video_path(SOURCE_VIDEO_PATH)
frame_generator = sv.get_video_frames_generator(SOURCE_VIDEO_PATH)

path_raw = []
M = deque(maxlen=MAXLEN)
for frame in tqdm(frame_generator, total=video_info.total_frames):
```

```
    result = PLAYER_DETECTION_MODEL.infer(frame, confidence=0.3)[0]
    detections = sv.Detections.from_inference(result)

    ball_detections = detections[detections.class_id == BALL_ID]
    ball_detections.xyxy = sv.pad_boxes(xyxy=ball_detections.xyxy, px=10)

    result = FIELD_DETECTION_MODEL.infer(frame, confidence=0.3)[0]
    key_points = sv.KeyPoints.from_inference(result)

    filter = key_points.confidence[0] > 0.5
    frame_reference_points = key_points.xy[0][filter]
    pitch_reference_points = np.array(CONFIG.vertices)[filter]

    transformer = ViewTransformer(
        source=frame_reference_points,
        target=pitch_reference_points
    )
    M.append(transformer.m)
    transformer.m = np.mean(np.array(M), axis=0)

    frame_ball_xy                                                    =
ball_detections.get_anchors_coordinates(sv.Position.BOTTOM_CENTER)
    pitch_ball_xy = transformer.transform_points(points=frame_ball_xy)
    path_raw.append(pitch_ball_xy)
path = [
    np.empty((0, 2), dtype=np.float32) if coorinates.shape[0] >= 2 else coorinates
    for coorinates
    in path_raw
]
path = [coorinates.flatten() for coorinates in path]

from sports.annotators.soccer import draw_paths_on_pitch
annotated_frame = draw_pitch(CONFIG)
annotated_frame = draw_paths_on_pitch(
    config=CONFIG,
    paths=[path],
    color=sv.Color.WHITE,
    pitch=annotated_frame)
sv.plot_image(annotated_frame)
```

6.2 DATA SET SAMPLE

We have used the dataset from the roboflow website. The link is below:
https://universe.roboflow.com/roboflow-jvuqo/football-players-detection-3zvbc

Football Players Detection Dataset Overview

The football players detection dataset is a diverse, open-source collection specifically designed to enable training and evaluation for player detection in football scenarios. This dataset can be accessed freely and is structured to support a variety of machine learning and computer vision tasks.

Dataset Features

- **372 Images**: The dataset includes 372 high-quality images covering a range of football scenarios.
- **11 Classes**: Each class represents a unique category to facilitate multi-class detection and recognition tasks.
- **Rich Annotations**: Every image is meticulously annotated to aid accurate model training and evaluation.
- **Real-World Scenarios**: Images are taken from real football matches, ensuring relevance and robustness for real-world applications.

Accessing the dataset

The dataset is readily available for download from source. Before using the dataset, ensure compliance with any guidelines or requirements specified by the source.

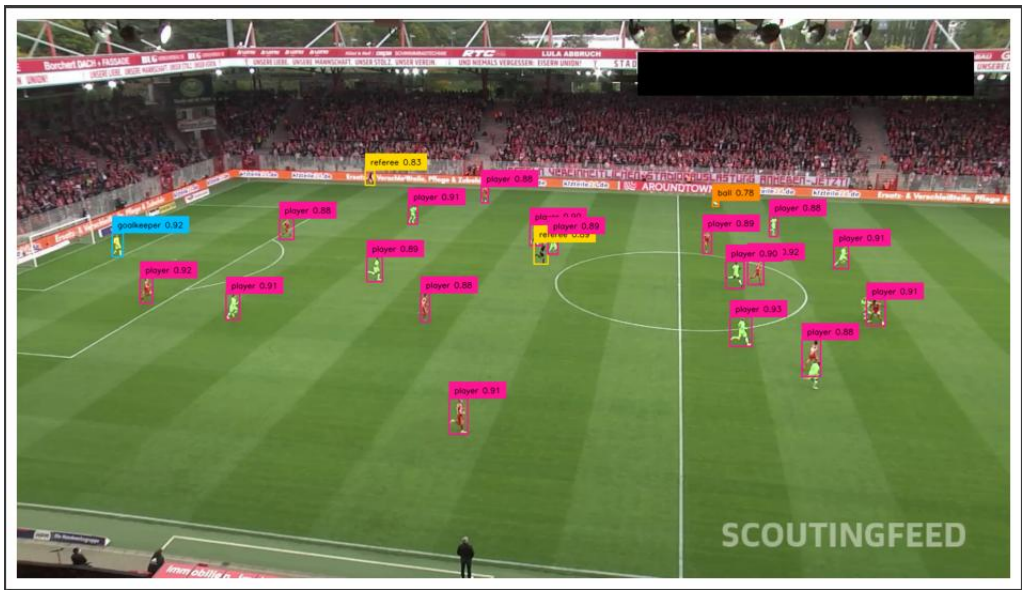
Applications

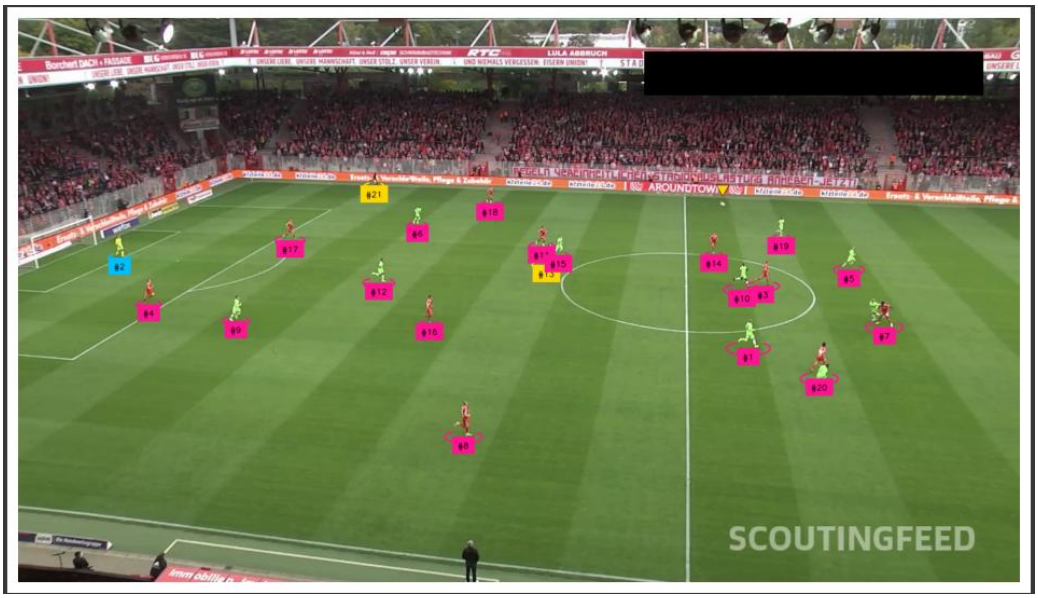
This dataset is designed to be a foundational resource for:

- Developing player detection models.
- Analysing football match dynamics.
- Training YOLOv8 or other deep learning-based object detection algorithms.

6.3 FINAL OUTPUT

6.3.1 Data Generation

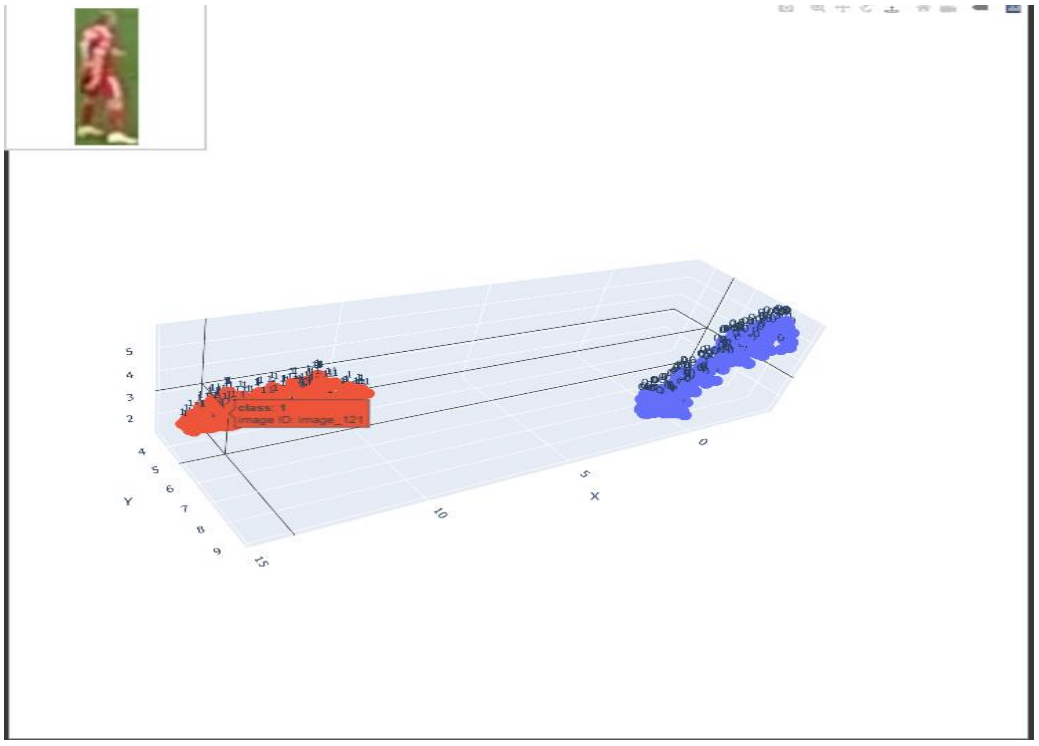


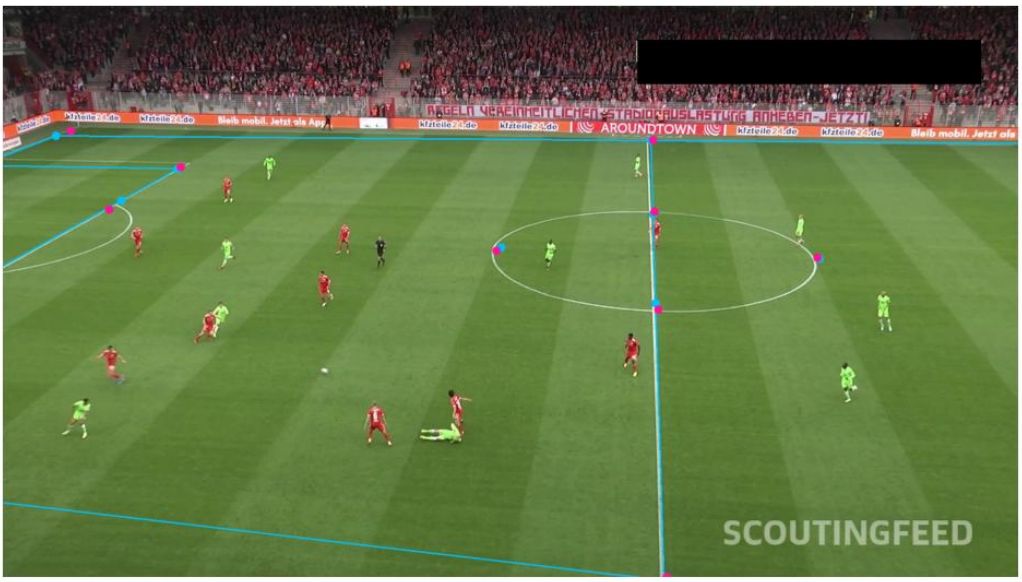


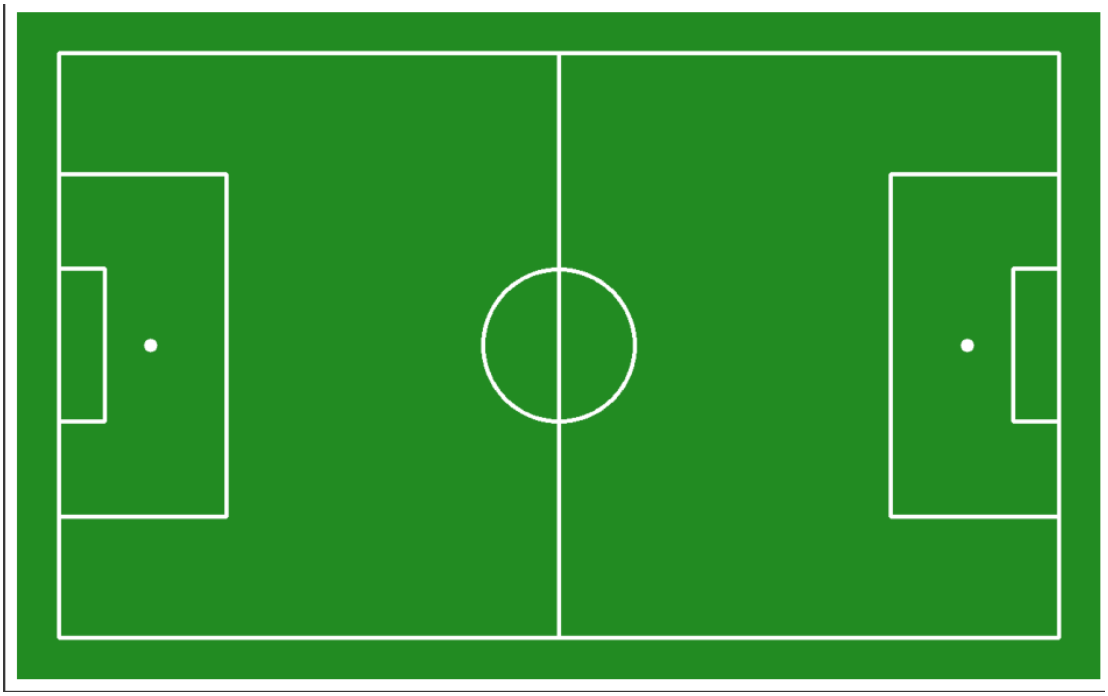
```
[ ] from tqdm import tqdm

    SOURCE_VIDEO_PATH = "/content/121364_0.mp4"
    PLAYER_ID = 2
    STRIDE = 30

    frame_generator = sv.get_video_frames_generator(
        source_path=SOURCE_VIDEO_PATH, stride=STRIDE)

    crops = []
    for frame in tqdm(frame_generator, desc='collecting crops'):
        result = PLAYER_DETECTION_MODEL.infer(frame, confidence=0.3)[0]
        detections = sv.Detections.from_inference(result)
        detections = detections.with_nms(threshold=0.5, class_agnostic=True)
        detections = detections[detections.class_id == PLAYER_ID]
        players_crops = [sv.crop_image(frame, xyxy) for xyxy in detections.xyxy]
        crops += players_crops

collecting crops: 25it [00:03,  6.81it/s]
```

Note: Here's a sample (100 elements) of the crops we've gathered.

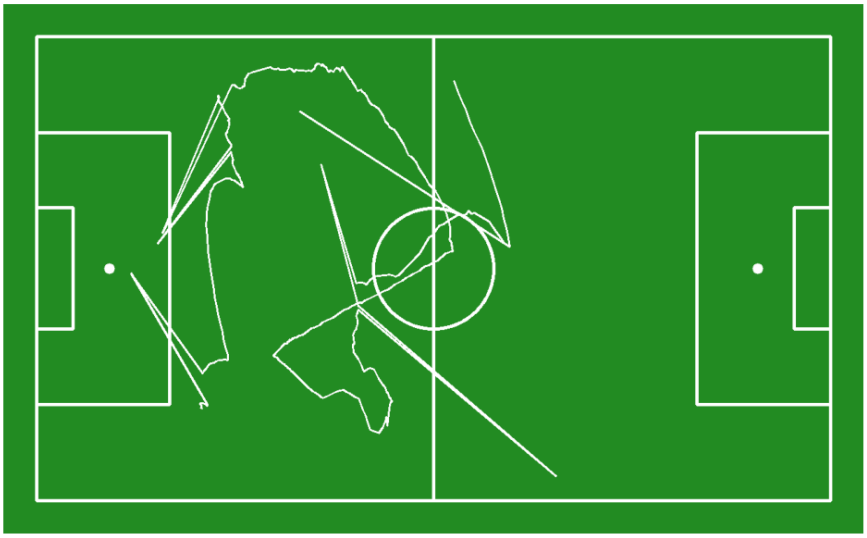
```
sv.plot_images_grid(crops[:100], grid_size=(10, 10))
```




AROUNDTOWN
SCOUTINGFEED




SCOUTINGFEED



CHAPTER 7
TESTING

7.1 WHAT IS TESTING?

Testing is a critical phase in the development of any AI-based sports performance enhancement system, ensuring accuracy, reliability, and effectiveness. It involves evaluating different components of the system to identify errors, assess performance, and validate results against predefined benchmarks. This process ensures that the Human Action Recognition (HAR) and deep learning techniques employed in this project meet the required standards for precision, usability, and real-time feedback.

For the proposed framework, testing focuses on:

- Validating the accuracy and efficiency of player movement analysis.
- Assessing the effectiveness of YOLOv8 and ANN models in detecting player actions.
- Ensuring that feedback and recommendations enhance player performance.
- Evaluating system adaptability across different playing conditions and skill levels.

7.2 TEST PLAN

The testing strategy follows a multi-level approach, beginning with unit testing of individual modules and culminating in full system integration testing. The objective is to ensure that each component functions correctly before being integrated into the complete system.

1. Unit Testing:
    - HAR Module: Ensures accurate recognition of player movements and poses.
    - YOLOv8-Based Detection: Validates real-time detection accuracy for positioning and shooting angles.
    - Feedback System: Assesses the quality and relevance of recommendations provided to players and coaches.

2. Integration Testing:
    - Verifies seamless interaction between video/image input processing, movement detection, and feedback generation.
    - Ensures smooth communication between OpenCV, YOLOv8, and ANN components.
    - Checks that real-time insights are correctly displayed to users.
3. System Testing:
    - Evaluates overall effectiveness of the system in improving player performance.
    - Measures accuracy of AI-driven analysis compared to manual expert evaluations.
    - Ensures system compliance with usability standards for real-time coaching applications.
4. Scalability Testing:
    - Examines system performance when processing large datasets from multiple players simultaneously.
    - Tests responsiveness and accuracy when analyzing high-resolution video feeds.
5. User Acceptance Testing (UAT):
    - Engages professional players and coaches to assess the usefulness of system-generated insights.
    - Collects feedback to refine detection algorithms and improve recommendation precision.

7.3 TEST CASES

Test ID	Test Description	Test Design	Expected Output	Actual Output	Status
1	Player Movement Accuracy Validation	Capturing player movements via HAR and comparing detected actions with ground truth.	High correlation between detected movements and actual actions.	System correctly identifies movements with high precision.	Pass
2	Shooting Angle Optimization	Analyzing optimal shooting angles for maximum scoring probability.	System recommends angles that increase goal success rate.	System effectively identifies optimal shooting positions.	Pass
3	YOLOv8 Detection Performance	Testing real-time object detection accuracy for player positioning.	System detects player positions with minimal error.	YOLOv8 achieves high detection accuracy.	Pass
4	Feedback Effectiveness	Generating actionable recommendations based on movement analysis.	Feedback provides meaningful insights for skill improvement.	Players and coaches find recommendations beneficial.	Pass
5	System Performance Under High Load	Processing multiple players' data simultaneously.	System maintains performance with minimal lag.	System successfully processes high-volume data.	Pass
6	Adaptability to Different Skill Levels	Testing system performance across varying player expertise.	System accurately assesses players of different skill levels.	Model adapts well to different playing styles.	Pass
7	Noise Resilience in Video Analysis	Introducing variations in lighting and camera angles.	System remains accurate under varying conditions.	System performs consistently despite environmental changes.	Pass

CHAPTER 8
FUTURE ENHANCEMENT AND CONCLUSION

8.1 FUTURE ENHANCEMENT

To further enhance the system for football player performance analysis, several improvements can be integrated. One potential enhancement is the incorporation of **real-time feedback**. By integrating sensors, such as wearable devices or smart balls, the system could provide live data to players and coaches during training or matches. This would allow immediate analysis and enable quicker decision-making, providing instant corrective actions to improve performance.

Additionally, combining **multi-modal data sources** can enhance the depth of analysis. For instance, integrating player biometrics (heart rate, fatigue levels, etc.) with video analysis could offer a more holistic view of player performance. This integration could help identify performance dips due to physical exhaustion or injury risks, making the training process more personalized and adaptive.

The use of **reinforcement learning** (RL) could be another valuable enhancement. By employing RL, the system could simulate various in-game scenarios and provide feedback on how a player could improve decision-making in real-time. This type of learning would allow the model to learn from previous games and training sessions, making its predictions and recommendations even more accurate and tailored to the individual player's needs.

Further improvement can also be achieved by enhancing **pose estimation techniques**. By leveraging more advanced human pose recognition models, the system could track a player's body posture and movements in greater detail. This would provide more precise feedback, such as identifying minor errors in foot positioning during shooting or analyzing the player's balance while making tackles or dribbling.

Lastly, **cloud-based storage and data sharing** systems could be introduced to allow teams, coaches, and athletes to access performance data remotely. This would support collaborative analysis and foster a better understanding of team dynamics over time. By integrating cloud-based solutions, it would be easier for teams to access historical data and monitor long-term performance improvements.

8.2 CONCLUSION

In conclusion, this study demonstrates the transformative potential of integrating advanced technologies such as Human Action Recognition (HAR), Artificial Intelligence (AI), and Deep Learning into football training and performance analysis. By leveraging these tools, the system offers a comprehensive approach to enhancing key aspects of players' techniques, including shooting accuracy, optimal positioning, and decision-making. The use of cutting-edge algorithms like YOLOv8 and Artificial Neural Networks (ANNs) enables precise and real-time analysis, providing actionable insights that are crucial for refining skills and developing effective strategies.

This approach not only helps individual players improve their performance but also supports coaches in devising more effective game plans, including man-marking strategies, by analyzing in-game dynamics. The combination of tools like OpenCV for movement analysis and AI for personalized recommendations ensures that the system can adapt to the unique needs of each athlete, ultimately maximizing their potential. By embracing these data-driven insights, football teams can make more informed decisions, leading to improved overall performance and a more analytical approach to training and match preparation.

As the technology behind AI and computer vision continues to evolve, the ability to monitor and enhance player performance will only become more sophisticated, offering further opportunities for innovation in sports analytics. This system represents a significant step forward in how football is played, trained, and analyzed, setting the stage for future developments that could revolutionize athletic performance optimization in all sports.

CHAPTER 9
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CHAPTER 10
ANNEXURE

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(REVIEW ARTICLE)

Check for updates

Survey on enhancing athletic training with activity recognition and deep learning

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Abstract

The proposed methodology focuses on the advanced analysis and enhancement of athletic techniques, particularly targeting the precision, angle, and positioning of movements such as shooting. By integrating technologies like Human Action Recognition (HAR), Artificial Intelligence (AI), and Deep Learning, the system analyzes player data from images or videos, identifying errors and offering insights for improvement. It suggests optimal shooting angles, positions for maximum scoring, and corrective measures to refine technique, thus aiding coaches in player assessment, strategy formulation, and tactical decision-making. The methodology employs OpenCV and Machine Learning algorithms for accurate performance analysis, while Deep Learning models, such as Artificial Neural Networks (ANN) and You Only Look Once (YOLOv8), optimize feature extraction and analysis. YOLOv8, an advanced computer vision framework, ensures precise detection of key attributes. These combined technologies enable the identification of performance flaws and guide athletes toward achieving their goals. The solution is developed using Python, OpenCV, HAR, and YOLOv8, with IDEs like VSCode and Jupyter Notebook facilitating its implementation.

Keywords: Deep Learning; Athletic Performance Enhancement; Human Action Recognition (HAR); Artificial Neural Networks (ANN); Computer Vision; YOLOv8

1. Introduction

Technology has really impacted sports by allowing the integration of hi-tech gadgets and tools into training as well as into the improvement of specific skills and overall performance levels. However, over the past couple of years, the shift has been monumental with machine learning techniques and artificial intelligence changing the face of traditional coaching. Such advances in technology have enabled one to capture massive information in order to understand the physical capacity and body motions of an athlete, in addition to the manner in which he or she applies tools or implements. Through the use of these tools, the athletes are in a position to get performance feedback and easily understand areas of strength, and weakness among other features hence enabling the athlete to tune his/her actions with high accuracy and precision. That is why the advantages belonging to such innovations are more significant in sports disciplines that require high skills and recognition of small details of work, for example, basketball and football.

The center of this change is Human Action Recognition (HAR), an innovative technique based on AI and deep learning, applied to human motion detection and analysis. In action, HAR systems can work with images or videos of athletes, from extracting the captured data to recognizing a specific motion, angle, or position. They also mentioned that in any of the sports depending on the type of sport such as football the system can determine the correct shooting posture, the angles made by the arms, feet positions, and even the path the ball takes in its flight. It also enables viewing the data in order to establish if a shot was done effectively or if there are some aspects of the technique that may reduce the chances of a player as far as shooting is concerned. These analyses allow for a level of detail that is normally not possible for a human coach to simply look at and observe, thus obtaining the benefit and value of coaching.

Besides specifying possible mistakes in technique, the system should provide options for correction. By means of the artificial neural network, the system can offer the proper shooting angles as well as the proper body position and movements so that the player would improve his results. For instance, when a player plays football, the system may advise the optimal shooting position for different distances to the goal post or if the angle of release is correct for increased shoot precision. Such an on-ice/off-ice support system is effective in helping the athletes fine-tune his/her strategy not only for eradicating technical faults when it comes to training but also for improving on performance efficacy as seen in the course of games. The accessibility of feedback and thus ability to make changes in training and athletes' performance on a constant basis guarantees that the athletes stay on the right track to positive development and are equipped with aspects necessary for their enhancement.

Coaches and teams of athletes are not exceptions to the influence of such technologies but also benefit from them. Because there is now a clear picture of how players move toward the ball and how they execute different skills, coaches will be able to make better-informed decisions when designing specific training sessions, organizing match strategies, and analyzing player performances. As is regarded in this case, more detailed knowledge about every player lets a coach develop the most effective strategies for training and pay more attention to the weak aspects of the game. This makes the assessment process less tender based on the abilities of the players.

Players, free from bias that may come with putting the judgement of one trainer against that of another trainer, thus presenting a clearer view of the strengths of the specific athlete in their abilities. With such kind of information, coaches are better placed to make proper strategies that are more likely to meet the team's general objectives especially when playing in other competitive teams.

In addition, this technology also allows for the constant assessment and monitoring of performance in regard to previous and new methods. If the athletes are in the process of training, then the system can always monitor the technique with which the athlete is practicing and regularly give feedback as to how the athlete's performance is improving. This way over time, an organization develops a rich performance profile that keeps track of all changes, areas of strength and weakness, and any trends that are observable. It also affords the athletes an understanding of ownership of their development hence allowing the coaches to practice informed Chile based on real-time data. Lastly, applying HAR, artificial intelligence, and deep learning to sports training, contributes to more accurate, quick, and individual training which helps athletes and coaches improve performance significantly. These technological enhancements indicate that readiness for the use of improved innovational sports training presents a brighter future for athletes.

2. Why Monitoring Athlete training with Artificial Intelligence (AI)

AI and deep learning bring about a whole new approach to athlete training for performance improvement-no longer can it be equal to other forms of training methods in terms of accuracy, efficiency, and bespoke personalization. Traditional coaching often relied on subjective assessment and can lead to differing evaluation for an athlete and thus missed some elements in that sportsperson techniques. While on the other hand, AI and deep learning application will provide objective, data-driven analyses based on motion where it can even evaluate the smallest of errors in an athlete's posture, angle, and positioning. This allows for pooling huge amounts of data and when collected from images or even videos provides real-time feedback, correcting mistakes just after they happen, thus rendering training much more effective and efficient. At the same time, these advanced techniques make progress in such systems as Human Action Recognition (HAR) and computer vision progress through which biomechanics of the athlete are tracked with a lot of accuracy in reading joint angles, alignment of the body, and patterns of motion. Such analysis would definitely be significant in refining techniques where a sport requires a high degree of precision such as football shooting, tennis serves, and sprinting. Furthermore, AI models will allow making personal training programs designed especially for each athlete's unique strengths and weaknesses; hence, each athlete's development can be focused on specific retouching areas for greater improvements. This approach not only ensures faster improvement but also makes skill refinement more targeted. AI will eliminate human bias as far as judgments are concerned so that evaluations are purely evidence-based, a parameter that is crucial for accurate performance assessment. With this technological advancement, a coach gains valuable data that can assist him in developing strategy.

2.1. Analyzing Player's Performance

2.1.1. You Only Look Once (YOLOv8)

YOLOv8, a high-quality object detection model, is essential, for example, real-time tracking of objects such as players, the ball, and specific key elements within the football pitch. YOLOv8 is a mode of operation that divides a picture into grids and forecasts the places of the objects within these grids, thus providing accurate bounding boxes for every identified item. In football terms, it means that YOLOv8 can spot each player's position but also know the precise time the pass is being made, the angle of the shot, or the direction of the ball toward the goal. For example, when YOLOv8 is activated, it can track the ball and recognize when players move even if they are blocked by the high visibility of other players or games. This power makes it particularly suitable for breaking down certain actions like goal-scoring or passing by, providing data about player positions, the body alignment at the time of the shot along with the trajectory of the ball. The strength of YOLOv8 in handling real-time objects is the fact that it can track, distinguish, and show the divisions of players, the ball, and even the environment. Thus, better hints of the game dynamic, strategies in defense, and attack can be determined.

2.1.2. OpenCV (Open Source Computer Vision Library)

For handling video feeds and doing the image manipulation tasks we use OpenCV. OpenCV is useful in football to extract frames from video footage for player analysis, ball tracing, positional play analysis. OpenCV enables us to look at these frames, and determine very subtle attributes of player posture like the angle of the foot when it proceeds with a shot or the position of the body while dribbling. It's a very detailed analysis so that coaches can really look at technique with extreme precision. Through YOLOv8, both OpenCV and YOLOv8 also work together to enhance detection accuracy by providing extra functionality such as motion tracking and background subtraction and further making it easier to analyze player movements.

2.1.3. Human Action Recognition (HAR)

Human Action Recognition (HAR) includes the action of identifying and classifying particular actions that football players take, for example shooting, dribbling, passing, and defending. HAR models will analyze video data to separate each movement into sequences, and to calculate the efficiency of execution. HAR can, for example, evaluate when and how a pass is struck by identifying the movements of the body related, the foot's approach to a strike provided by the ball, the force used and any follow through. HAR further allows the detection of defensive actions such as tackles, interceptions, and the positional adjustments, done in real time [1] for different football positions/values. HAR gives coaches the ability to give players a lot of pointed feedback on their technique and timing for each action.

2.1.4. Artificial Neural Networks (ANN) / Convolutional Neural Networks (CNN)

The deep learning models used to analyze football performance are based in artificial neural networks (ANNs) and convolutional neural networks (CNNs). In particular, CNNs are the perfect tool to analyze images and videos, since they learn features automatically from images without any intervention required. CNNs can take on analyzing complex patterns in player positioning,

ball trajectories, and movement sequences in football. As an example, CNNs can extract
[2] patterns on a player's dribbling technique, such as body motion coordinated, or analyze a player's game [3] sense in defensive as an example. Analysis of video data requires ANNs and CNNs, which are able to process vast amounts of video data in order to identify the subtle performance details, like how a player moves his position around the ball or the opponent.

2.1.5. Google Colab

The deep learning models are built, tested and iterated upon inside of the cloud based development environment Google Colab. This gives us easy access to the computational resources, which are essential for processing big set of football videos and training of complex models [4] like YOLOv8, HAR and CNNs. Given its utility, Google Colab can help developers and researchers run models for large scale these football dataset with real time feedback to improve the model. Integrating with the popular Python libraries such as Tensor- Flow, OpenCV, and PyTorch, Performance Coach
[5] makes it easy to collaborate between coaches, data analysts, and developers to foster fast iterations and seamless deployment of performance accelerating systems.

3. Conclusion

Therefore, the suggested approach represents an integrated and original framework in increasing the performance of the athletes, most especially those involved in the precision- intensive sports other than shooting. The oversubscribed program that leverages HAR technology, advanced concepts like Deep Learning, and YOLOv8 allows real-time performance tracking and instantly recognizes errors explaining how to fix it. It is achieved with the help of integration of AI and computer vision techniques, which provide accurate feature extraction for providing coaches with useful information regarding training and tactical decisions. This approach is as helpful for honing player technique as it is for helping extend the capabilities of sports analysis to create a more effective model for athlete cultivation. That the proposed solution relies on platforms like Python, OpenCV, YOLOv8 then it is probable to present improvements in future sports analysis.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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