Deep Learning and Computer Vision in Entertainment (Football)

By Daniel Damunza & Wayne Chilionje.

1. Problem

1.1 Background

Football analytics has evolved to provide deeper insights into player performance, team dynamics, and recruitment strategies. Models like **StatsBomb's OBV (On-Ball Value)** offer groundbreaking ways to assess player contributions beyond traditional statistics. Similarly, in football simulation games like FIFA, the challenge

of optimizing team performance using chemistry, stats, and playstyle highlights the potential for advanced analytics.

1.2 Challenge

- In real-world football: Quantifying the value of every action to enhance recruitment and tactical decision-making.
- In FIFA: Analyzing player data, team chemistry, playstyle preferences, and match performance to identify the optimal team composition.
- Shared challenges: Handling large datasets, ensuring accurate predictions, and optimizing team performance based on complex interdependencies between players.

1.3 Solution

Deep learning offers a robust solution for both real-world football analytics and FIFA optimization. By utilizing models like OBV for real-world data and deep learning frameworks for virtual simulations, it is possible to:

- Quantify every on-pitch action's value.
- Recommend data-driven player recruitment strategies.
- Optimize team composition by balancing player attributes, chemistry, and formation.

Deep learning and computer vision have a role to play in football, and they provide advanced analytical tools for:

- Player and ball tracking
- Scouting and recruitment
- Optimizing Fifa teams

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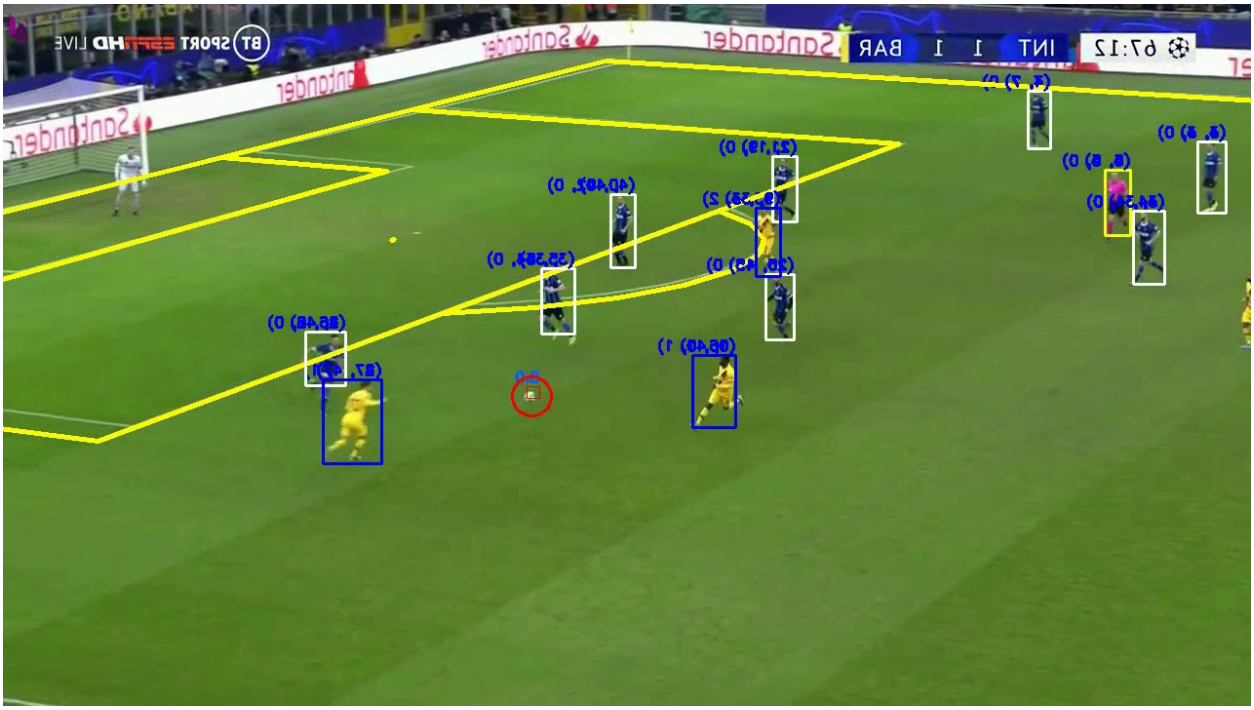
2. Use Cases

2.1 Player and Ball Tracking

- **Player Tracking:** Deep learning models, particularly convolutional neural networks (CNNs), are used to detect and track players on the pitch. These

models process video footage to identify player positions, movements, and trajectories throughout a match. Tracking data helps analyze player performance, fitness levels, tactical positioning, and space utilization.

- **Ball Tracking:** Similar models are used to track the ball's movement, velocity, and trajectory. Accurate ball tracking allows for detailed analysis of passes, shots, and set pieces.
- Basic framework behind ball and player tracking tasks:
    - **Reference system** and homography estimation (how to *project* players position from camera-view to a 2D plane).
    - **Object detection** (aka what and where are the players/ball/referee).
    - **Object tracking** (aka how do I track entities across frames).
    - **Player Identification** (aka how do I recognise the players across frames).
    - **Team Recognition** (how do I figure what team does a player play for).

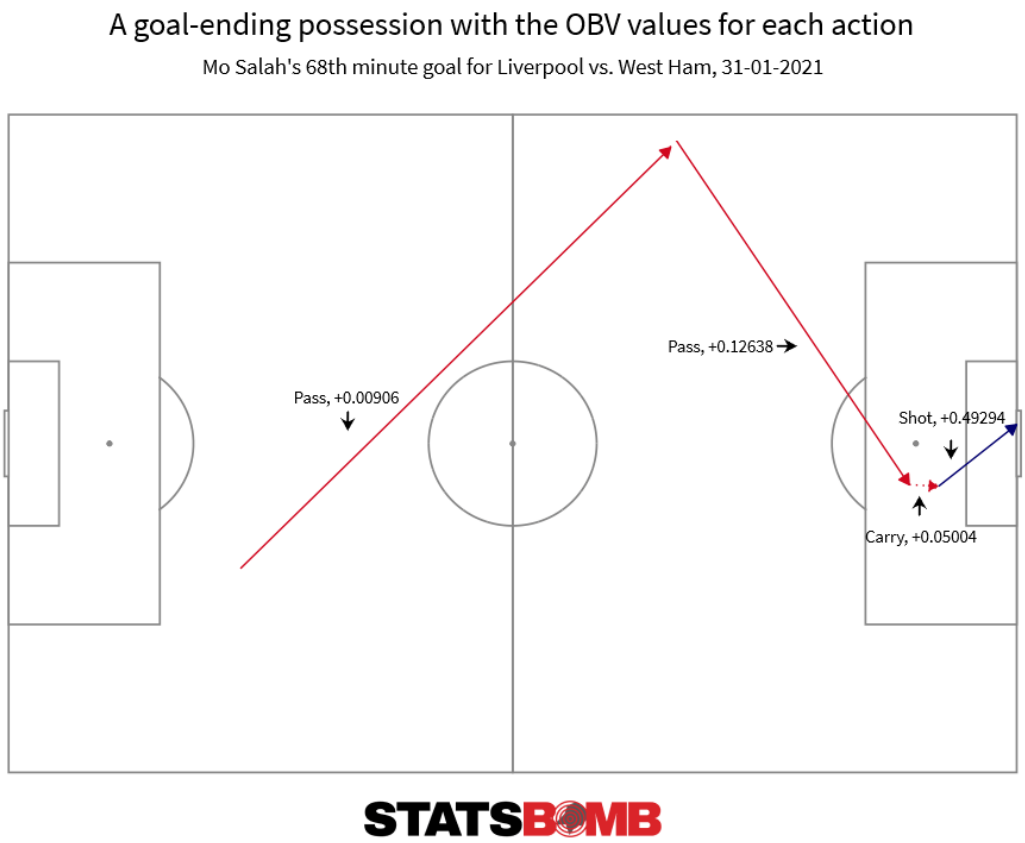


2.2 Scouting and Recruitment

- **Performance Metrics:** Deep learning algorithms analyze vast amounts of data to provide insights into player performance. By evaluating metrics like speed, stamina, passing accuracy, and shooting efficiency, clubs can identify potential recruits that fit their style of play.
- **Player Comparison:** Advanced models compare players across different leagues and competitions, helping scouts identify talent that traditional scouting methods might overlook. This comparison is based on various performance metrics captured through computer vision.

2.3 Use of RNNs and Deep Learning Models in OBV

- **OBV** calculates the value of each action based on its impact on the team's likelihood of scoring and conceding.
- **Variables** used include:
  - Location on the field
  - Type of action (pass, dribble, tackle, etc.)
  - Game state (score, time remaining)
  - Player positioning and movement
- **Sequential Data:** Football actions occur in sequences, where the context of previous actions affects the value of the current one. **RNNs** are well-suited for this task as they can handle sequential data, making them ideal for understanding the flow of a game and predicting the value of each action based on the sequence leading up to it.



2.4. Making the best Fifa team

- In parallel, deep learning is also revolutionizing how optimal team compositions are selected in **FIFA**, a popular football simulation game.
- By analyzing player data, team chemistry, playstyle preferences, and match performance metrics, a deep learning model can recommend the best team lineup.
- This model, developed using data from FIFA 22, optimizes team performance by balancing player stats, chemistry, and formation for the best synergy, much like OBV does in real-world scenarios.

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3. Implementation

3.1 Scope

- **OBV:** Measures the value of every action in football to guide recruitment.

- **FIFA Optimization Model:** Considers player attributes, chemistry, formation compatibility, and opponent data to generate tailored strategies.
- Both approaches focus on improving performance, decision-making, and team success.

3.2 Data Collection

- **OBV Model:**
  - Uses event data and tracking data from matches.
  - Examples: Passes, shots, dribbles, and xG-related metrics.
- **FIFA Optimization Model:**
  - Sources player attribute data from FIFA 22.
  - Includes stats like speed, passing, dribbling, and chemistry metrics.

3.3 Preprocessing

- Normalize data to a consistent scale (e.g., [0, 1]).
- Encode categorical variables like player positions, clubs, and leagues.
- For FIFA, calculate features like **chemistry** and **formation compatibility.**
- For OBV, preprocess event data to contextualize each action (e.g., match state, opponent pressure).

3.4 Model Design

- **OBV Model:**
  - **Feature extraction**: Analyze on-ball actions.
  - **Prediction**: Use sequential models like RNNs to quantify action value.
  - **Optimization**: Identify players with the highest OBV impact.
- **FIFA Optimization Model:**
  - **Feature extraction**: Player stats and synergy factors.
  - **Synergy calculation**: Optimize chemistry and formation.
  - **Prediction and optimization**: Generate lineups maximizing win probabilities.

3.5 Model Evaluation

- **OBV:**
  - Compare the model's evaluations against expert scouting reports.
  - Evaluate its impact on recruitment decisions and match outcomes.
- **FIFA Optimization Model:**
  - Assess match win rates with generated teams.
  - Evaluate improvements in chemistry and lineup effectiveness.

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4. Technologies Involved

- **CNNs:** For image and video recognition tasks.
- **Recurrent Neural Networks (RNNs):** For analyzing sequences of events and predicting future actions.
- **Object Detection Algorithms:** Like YOLO (You Only Look Once) or Faster R-CNN for real-time detection and tracking of players and the ball.
- **LSTMs** and **GRUs** - well-suited for capturing long-term dependencies in sequences which is key because in football, even the smallest actions early on in a sequence have a role to play in scoring a goal.

5. References

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