

**Faculty of Computers & Benha University**

**Artificial Intelligence**

**AI Soccer 3 V 3 Football Game**

A Fun Soccer Game Powered by Smart Reinforcement Learning AI

***Project Team***

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**1. Background and Motivation**

This project focuses on building a 3v3 soccer game simulation using the Pygame library and AI techniques. We use reinforcement learning to train an AI that controls two teams: Red and Blue. Each team has two field players and one goalkeeper, competing to score goals by passing and shooting the ball.

The motivation behind this project is to explore how AI can manage complex, dynamic games like soccer, which require teamwork, strategy, and quick decisions. We aim to evaluate the AI’s ability to score goals, work as a team, and handle game challenges. The simulation provides a controlled environment to test AI learning and performance in a sports context.

However, the original code had problems with tracking scores and rewards, which made it hard to assess the AI’s performance accurately. This report addresses these issues, detailing the fixes and analyzing the results to understand how well the AI performs in this soccer simulation.

**2. Introduction**

The AI Soccer Simulation project uses reinforcement learning with the PPO algorithm from the Stable-Baselines3 library. The simulation creates a soccer match where the AI controls all players’ actions, including moving, passing, and shooting. The Red team (with players Elnemr, Beherry, and Red\_GK) competes against the Blue team (Abanoub, ElShokary, and Blue\_GK) to score goals.

The simulation tracks scores, rewards, and match events to measure the AI’s performance. Rewards are given for scoring goals, passing, and positioning. However, the original code had issues with the reward system and goal reporting, such as incorrect team rewards and missing goal details. This report explains these problems, the steps taken to fix them, and the updated results, which show a final score of Red: 10, Blue: 15, with a total reward of 441926.54.

**3. Problem Statement**

The original code for the AI Soccer Simulation had significant issues in the evaluate\_match function, which summarizes match results:

- Team rewards were incorrect, showing 0 for both teams despite a final score of Red: 10 - Blue: 15, which should have given Red 10000 points and Blue 15000 points (1000 per goal).

- Goal details were not displayed properly, showing "The Match Is Finished" instead of listing the 25 goals scored during the match.

- The reward system mixed goal rewards (1000 points) with other rewards like passing and positioning, leading to errors in tracking team performance.

Our goal was to fix these issues to ensure accurate reward tracking, proper logging of all goals, and a clear match summary, allowing us to evaluate the AI’s performance more effectively.

**4. Methodology**

**4.1 Problem Analysis**

We identified three main problems in the code:

- The evaluate\_match function used the total reward, mixing goal rewards with other rewards like passing bonuses, causing incorrect team rewards.

- Goal detection in \_check\_goal wasn’t properly linked to the reward calculation in \_calculate\_rewards, leading to timing issues.

- The goal\_details list used the total step reward instead of the goal-specific reward (1000 points), and the summary logic failed to show all goals.

**4.2 Solution Approach**

We implemented these solutions:

- Updated \_calculate\_rewards to return total reward, goal reward (1000 points), and the scoring team separately.

- Modified step to include goal reward and scoring team in the info dictionary for evaluate\_match to use.

- Fixed evaluate\_match to use goal reward for team rewards and to list all goals in the final summary, removing the incorrect message.**5. Updated Code Overview**

We made changes to three key functions to improve the simulation:

- \_calculate\_rewards: This function now returns a tuple with the total reward (including all rewards), goal reward (1000 points for a goal, 0 otherwise), and the scoring team (e.g., 'red' or 'blue'). This separates goal rewards for accurate tracking.

- step: This method now includes the goal reward and scoring team in the info dictionary, which is passed to evaluate\_match for processing.

- evaluate\_match: This function uses the goal reward to update team\_rewards (e.g., 10000 for Red, 15000 for Blue) and lists all goals in goal\_details with the correct reward, team, and player.

These updates ensure that the simulation accurately tracks rewards and reports all goal events, making the results more reliable for analysis.

**6. Results**

**6.1 Match Output**

The original match output was:

Final Score - Red: 10 - Blue: 15

Total Reward: 441926.54

The Match Is Finished

Accuracy: 100.00%

After the fixes, the output is improved:

Final Score - Red: 10 - Blue: 15

Total Reward: 441926.54

Goal Details: Lists all 25 goals with team, player, and reward

Team Rewards - Red: 10000, Blue: 15000

Accuracy: 100.00%

**6.2 Analysis**

- Team Rewards: Red has 10000 points (10 goals × 1000), and Blue has 15000 points (15 goals × 1000), matching the score.

- Total Reward: 441926.54 includes 25000 from goals and 416926.54 from other actions like passing and positioning.

- Goal Details: All 25 goals are now shown, with details like "Goal 1 by Red Team (Player: Elnemr) - Reward: 1000.00".

**7. Performance Evaluation**

**7.1 AI Performance**

The AI performed well in the match:

- It scored 25 goals in total, with Blue scoring 15 and Red scoring 10, showing strong offensive skills.

- The extra 416926.54 points (beyond goal rewards) indicate good passing, ball control, and positioning by the AI.

- The Blue team’s higher score suggests better teamwork between Abanoub and ElShokary, possibly with smarter use of Blue\_GK.

**7.2 Reward System**

The updated reward system works effectively:

- Goal rewards are accurately tracked at 1000 points per goal.

- High extra rewards show the AI’s ability to handle non-scoring tasks like passing and positioning.

- The system encourages both scoring and teamwork, helping the AI learn balanced gameplay.

**8. Discussion**

**8.1 Effectiveness of Fixes**

The fixes improved the simulation significantly:

- Team rewards now correctly reflect the score: Red at 10000 and Blue at 15000 points.

- Goal details list all 25 goals with the scoring team, player, and reward, making the summary clear.

- The simulation is now a reliable tool for evaluating the AI’s performance in soccer.

**8.2 Limitations**

There are still some limitations:

- The accuracy metric is 100% because max\_reward\_per\_match (25000) is too low for a total reward of 441926.54.

- Goal attribution uses only the last kicker, which might miss contributions from other players.

- The 25 goals in one match make the game less realistic, as real soccer matches have fewer goals.

**9. Recommendations**

9.1 Adjust max\_reward\_per\_match

Increase max\_reward\_per\_match to 500000 to improve accuracy:

- New accuracy would be (441926.54 / 500000) × 100 = 88.39%.

9.2 Enhance Reward Tracking

Add tracking for passing and defensive actions like tackles. Include penalties for mistakes like losing the ball.

9.3 Improve Realism

Reduce the number of goals by adjusting settings like kick power and friction. Improve goal attribution to consider the whole play.

9.4 Visual Enhancements

Add real-time reward displays and player stats (e.g., goals, passes) on the screen for better analysis.

**10. Conclusion**

The AI Soccer Simulation project successfully fixed the issues with reward tracking and goal reporting. The updated simulation now accurately shows team rewards (Red: 10000, Blue: 15000) and lists all 25 goals in the match (Red: 10, Blue: 15). The total reward of 441926.54 reflects strong AI performance in both scoring and non-scoring actions.

The Blue team’s lead suggests better teamwork, but the high goal count indicates a need for more realistic defense. Recommendations include adjusting the accuracy metric, enhancing rewards, and improving game realism. This simulation is now a solid tool for studying AI in sports, with room for further enhancements.