# Snake AI: Teaching an AI to Play Snake Better Than Humans

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**Abstract**

This study investigates how Genetic Algorithms (GAs) can be used to train a neural network to play the Snake game and whether it can outperform human players. The AI was trained on a 20×20 grid, and it achieved an average score of 46.21 (food collected) where the human average was only 13.91. The AI also survived longer, averaging 1169.12 steps per game, while humans averaged 301.90 steps. The results show that the AI's better path planning, developed through GA optimization, gave it a clear advantage over humans. For future research it can be interesting to understand how experimenting with different hyperparameters or model designs can help improve the AI's performance even further.

## 1 Introduction

Over the past decade, artificial intelligence (AI) has experienced significant growth, with advancements in generative AI driving its potential to transform industries and outperform humans in complex tasks (McKinsey & Company [1]). This trend has sparked interest in exploring AI's capabilities across various domains, particularly in areas requiring precision and speed. One such domain is gameplay, where AI can process information and make decisions more efficiently than humans, offering a promising possibility to test its abilities.

The Snake game presents a classic challenge where a snake navigates a 20×20 grid to eat food, growing longer with each piece while avoiding collisions with walls or its own body. The objective is to maximize the score by collecting as much food as possible and surviving for as long as possible, a task that becomes increasingly difficult as the snake grows. Snake serves as an effective testbed for AI techniques due to its requirement for both rapid decision-making and strategic planning - skills that often challenge human players. This study employs genetic algorithms (GAs) to train a neural network to play Snake, with the aim of determining whether AI can outperform human players. The primary goal is to compare AI performance with that of human players and to analyze differences in their strategies, providing insights into the effectiveness of GA-trained AI in gameplay scenarios.

## 2 Research Question/Problem Formulation

To understand the ongoing discussion on AI's superiority, this study will investigate:
Can a Genetic Algorithm train a neural network to play the Snake game better than

human players?
As sub-questions, it is relevant to look into some of the underlying mechanisms to obtain a truly holistic result. Therefore, the study will also try to understand:

1. How do AI and human strategies differ?
2. Does human performance improve enough with practice to match the AI?

The AI is trained with a Genetic Algorithm to optimize its decision-making, while humans rely on personal strategies and reflexes.
Performance is measured by the score (amount of food collected) and survival duration (number of steps taken before the game ends).

# 3 Methods

This section outlines the steps taken to address the research question, adapting the data science process described by AJ Goldstein [2] to fit the optimization-focused nature of this project.

## 3.1 Step 1: Frame the Problem

The first step was to define the problem clearly. This study addresses the challenge of determining whether an AI, trained using genetic algorithms (GAs), can outperform human players in gameplay scenarios, a domain where AI's ability to process information and make decisions rapidly offers a potential advantage. The Snake game was selected as a testbed to explore this question due to its requirement for both rapid decision-making and strategic planning, making it a suitable challenge to evaluate AI's capabilities against human performance. The objective was to train an AI to play Snake and compare its effectiveness with that of human players, focusing on differences in gameplay strategies and overall performance.

## 3.2 Step 2: Design the GA and Neural Network

This step involved setting up the neural network and the game environment for the experiment. The neural network architecture consists of an input layer with 21 neurons (e.g., snake position, food location, wall distances), three hidden layers (128, 64, 32 neurons) with Leaky ReLU activation, and an output layer with 4 neurons (movement directions) using softmax, starting with random weights. The Snake game environment was adapted from sample code provided by H. Strøm [3], implemented on a $20 \times 20$ grid. In this setup, the snake can move in four directions (up, down, left, right), and the game terminates if the snake collides with a wall or its own body. Each food item collected increases the score by 1. Different GA configurations were tested to optimize the neural network's performance, as detailed in the next step.

## 3.3 Step 3: Train the AI using GA

Several setups were tested with different population sizes (150, 160, 170), mutation rates (0.035, 0.032, 0.03, 0.028), generations (100–300), and games (5–10) per model, using a fitness function based on score and steps to evaluate training performance. In this context, fitness is a composite score that quantifies a neural network's overall performance in the game, guiding the GA's evolutionary process by determining which models are selected for crossover and mutation. The best model, saved as `model_2_pop150_mut0.03.pkl`, was automatically selected by evaluating all models on 10 new games and fine-tuned for another 50 generations (mutation rate 0.03), stopping when improvements were small, saving the result as `best_model.pkl`. Multiprocessing was used to speed up the training process.

### 3.4 Step 4: Collect and Process Performance Data

The study collected human performance data: 34 valid games from 3 participants. The 3 participants had varying experience levels: Kathrine (level 5), Frederik (level 7), and Jesper (level 8). This allowed the study to explore how experience affects performance. The human data was collected over multiple sessions for each player, resulting in 34 valid games. Human games with a score of 0 were filtered out as potentially unfair (e.g., non-attentive to the gameplay), and data was formatted consistently using `human_performance.py`. The detailed human results, including scores and steps for each game, were saved in `human_results.json`. The AI evaluation data (34 games) was collected during the final experiment in Step 5.

### 3.5 Step 5: Analyze the Performance Data

The study compared the AI and human performance using the `run_final_experiment` in `experiment_manager.py`, which runs 34 evaluation games for the AI and compares them to 34 human games. It logs the training and evaluation results to the console and saves detailed statistics in `enhanced_model_final_eval_34games.pkl`.

### 3.6 Step 6: Communicate Results

Findings are presented in the Findings and Conclusion sections, summarizing performance and implications.

## 4 Analysis

In the final evaluation with 34 games (to match the 34 human games for a fair comparison), the AI got an average score of 46.21 ($\pm$9.09), with a high of 61 and a low of 18, while humans averaged 13.91, with their best at 45 and lowest at 1 (excluding zero scores). For survival, the AI lasted an average of 1169.12 steps, compared to a human average of 301.90 steps. After continued training, the best model had a training score of 57.14 and 1455.29 steps over 5 games, but its validation score during model selection was 36.60 over 10 games. The results are summarized in Table 1, which shows the performance gap.

Table 1: Performance Metrics

| Metric | AI | Human |
|---|---|---|
| Avg. Score | 46.21 | 13.91 |
| Max. Score | 61.00 | 45.00 |
| Avg. Steps | 1169.12 | 301.90 |

The AI stood out in how it played. It planned paths carefully, often taking longer routes to avoid crashes while grabbing food, which helped it score higher and survive longer. Humans usually reacted on the spot, leading to more crashes and lower scores. It was noticed that humans had different strategies—some went straight for the food to save time, while others moved carefully to avoid collisions. However, even after several rounds of practice, their scores didn't improve much to get closer to the AI's consistent performance.

The training score (57.14) and steps (1455.29) were about 20% higher than the evaluation score (46.21) and steps (1169.12), suggesting some overfitting. The validation score (36.60) was even lower, showing the model improved after fine-tuning but still struggles in some scenarios mostly due to trapping itself. The evaluation scores varied between 18 to 61. However, the AI still outperformed humans by 32.29 points on average, showing it learned effective strategies.

**Figure 1a** shows the AI's scores mostly between 40 and 60 (median 46.50), while human scores were 1 to 30, with a few up to 45.

**Figure 1c** shows human scores by experience level. Levels 7 and 8 improved to 20–25 from 10–15, but stayed below the AI's 46.21. Level 5 player obtained best performance.

**Figure 1b** plots steps vs. scores, with the AI at higher steps (800–1600) and scores (40–61), while humans were below 500 steps and 20 points.

**Figure 1d** tracks human learning curves. They improved more than twice from first to second session but then plateaued.

# 5 Findings

The results from the analysis revealed several key points:

- The AI outperformed humans, averaging 46.21 compared to the human average of 13.91, with a highest score of 61 versus 45.
- The AI survived longer, averaging 1169.12 steps per game versus 301.90 for humans.
- The AI planned paths effectively, avoiding collisions, while humans often made reactive decisions, leading to crashes.
- Human performance improved with practice, reaching a maximum score of 45, but remained below the AI's average.
- Humans struggled with food on the sides or corners, requiring quick reflexes, whereas the AI handled these scenarios effectively.

# 6 Conclusion

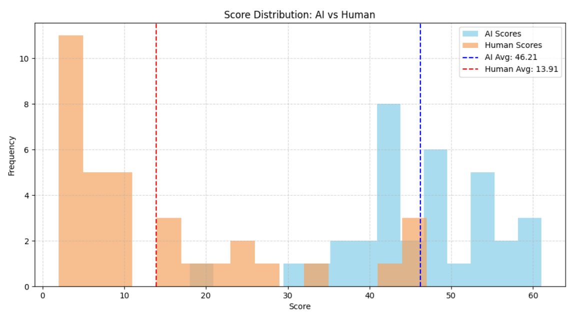
This project demonstrated that a genetic algorithm can train a neural network to play Snake more effectively than humans, with the AI achieving superior scores and survival times. The AI has more efficient strategies than humans as it is able to plan, act and react more controlled than humans. The study is not able to conclude on whether humans become good enough with additional training to catch up to the AI due to a low sample and few games. The AI's path planning and grid utilization highlight the potential of GAs in game AI applications. The limited human sample size (3 participants, 34 valid games after filtering) suggests future work with more players to assess the performance gap. Extended human training might also improve scores, and further optimization of the GA settings could enhance the model.

# References

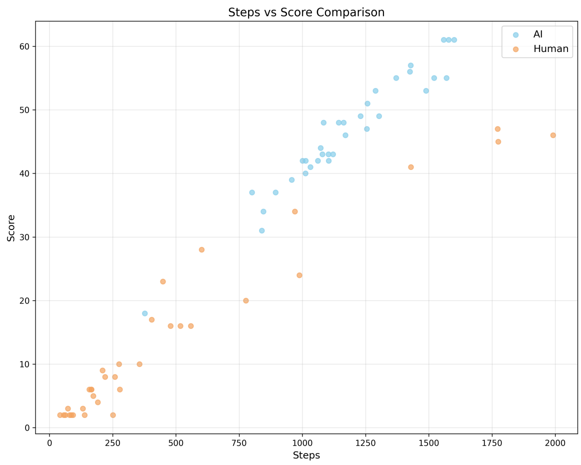

[1] McKinsey & Company. (2023). *The economic potential of generative AI: The next productivity frontier.* Retrieved from `https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier` (Accessed: 27 May 2025)

[2] AJ Goldstein (2017). *Deconstructing Data Science: Breaking The Complex Craft Into Its Simplest Parts.* Medium.com.

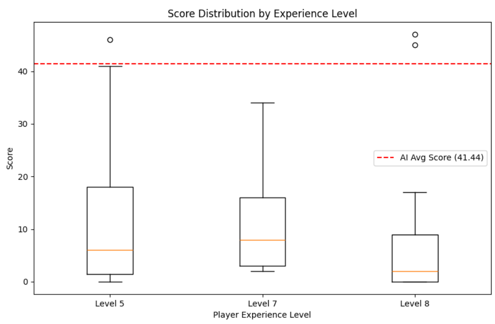
[3] Strøm, H. (2025). *Snake AI Sample Code (ga-model branch).* GitLab Repository. Available at: `https://gitlab.com/keaorg/snake/-/tree/ga-model?ref_type=heads` (Accessed: 21 May 2025).

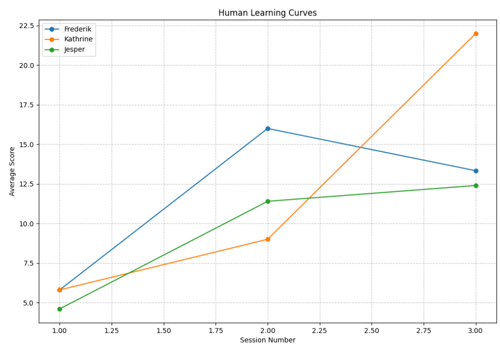

(a) Score distribution for AI and humans.




(b) Steps taken vs. scores for AI and humans.




(c) Score distribution by experience level.




(d) Human learning curve.

Figure 1: Performance comparisons for AI and humans.