



# Khulna University of Engineering & Technology (KUET)

Department of Computer Science & Engineering

## AI vs AI Survival Arena

A Multi-Algorithm Game Simulation Using A\*, Minimax, and Fuzzy Logic

**CSE 4000: Artificial Intelligence Project**

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November 2, 2025

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## Abstract

The AI vs AI Survival Arena is an autonomous game simulation that demonstrates the integration of three fundamental artificial intelligence algorithms: A\* pathfinding, Minimax with alpha-beta pruning, and Fuzzy Logic decision-making. This project implements a turn-based strategy game where two AI-controlled players compete on a 20×20 grid battlefield while navigating hostile enemies, collecting resources, and making strategic decisions in real-time.

The system architecture employs a modular design where each AI algorithm serves a distinct purpose. A\* pathfinding is utilized by ally bots for optimal resource collection, ensuring efficient navigation through obstacle-filled terrain. The Minimax algorithm with alpha-beta pruning powers enemy agents, enabling them to make intelligent targeting decisions by evaluating multiple moves ahead while optimizing computational efficiency. Fuzzy Logic governs the strategic decision-making of the main AI players, processing continuous input variables such as health status, score differential, and enemy proximity to produce human-like tactical behaviors.

The implementation features a modern graphical user interface built with Pygame, displaying real-time game state visualization through a card-based UI layout with custom PNG assets. The game mechanics include dynamic resource spawning, collision detection, health management, and multiple victory conditions. Experimental results demonstrate emergent strategic behaviors arising from the interaction of these algorithms, including tactical positioning, resource prioritization, and adaptive enemy avoidance. Over 50 test matches, score victories dominated at 62%, with average game length of 32.4 turns, demonstrating well-balanced gameplay. Computational performance analysis shows that Minimax consumes 58.8% of turn execution time at 8.7ms, while A\* and Fuzzy Logic remain efficient at 2.1ms and 0.3ms respectively.

This project serves both as an educational demonstration of AI algorithm integration and as a testbed for evaluating the performance characteristics of different algorithmic approaches in a competitive game environment.

**Keywords:** Artificial Intelligence, A\* Pathfinding, Minimax Algorithm, Alpha-Beta Pruning, Fuzzy Logic, Game AI, Autonomous Agents, Python, Pygame

# 1 Introduction

## 1.1 Background and Motivation

Artificial intelligence in game development represents one of the most visible and accessible applications of AI research. Game AI serves dual purposes: creating engaging player experiences and providing testbeds for algorithmic research. Traditional game AI systems often rely on scripted behaviors or finite state machines, which can produce predictable and limited behavior patterns. Modern approaches increasingly incorporate classical AI algorithms such as pathfinding, adversarial search, and fuzzy reasoning to create more sophisticated and emergent behaviors.

This project explores the integration of three foundational AI algorithms within a unified game environment. A\* pathfinding addresses optimal navigation, Minimax with alpha-beta pruning handles strategic adversarial decision-making, and Fuzzy Logic provides human-like reasoning under uncertainty. By combining these approaches in a competitive arena setting, we demonstrate how complementary AI techniques can produce complex emergent behaviors that exceed the capabilities of any single algorithm.

## 1.2 Problem Statement

The challenge addressed by this project involves three key aspects. First, algorithm integration requires combining fundamentally different AI algorithms into a cohesive system that produces coordinated intelligent behavior. Second, strategic decision-making necessitates AI agents that can balance multiple competing objectives including health preservation, score accumulation, and tactical positioning without explicit programming of every scenario. Third, emergent complexity seeks to determine whether the interaction of relatively simple algorithmic components can produce sophisticated strategic behaviors that exhibit adaptation over the course of a game.

## 1.3 Objectives

The primary objectives of this project are to implement a fully autonomous AI vs AI game where both players are controlled by artificial intelligence without human intervention, integrate three distinct AI algorithms in a modular architecture that allows independent algorithm evaluation, develop a Fuzzy Logic decision system that produces strategic behaviors from continuous input variables, implement A\* pathfinding with Manhattan distance heuristic for optimal navigation through obstacle-filled terrain, create a Minimax adversarial search with alpha-beta pruning for enemy targeting decisions, design a real-time visualization system that clearly displays AI decision-making processes and game state, demonstrate emergent strategic behaviors arising from algorithm interaction,

and provide comprehensive documentation suitable for educational purposes and future extension.

## 1.4 Scope and Limitations

This project encompasses turn-based gameplay on a discrete  $20 \times 20$  grid with two AI players representing distinct teams. The system includes four ally bots for resource collection, four enemy agents with adversarial behavior, and dynamic resource spawning including health packs and coins. Multiple victory conditions are supported including score threshold, elimination, and time limit scenarios, all visualized through a real-time modern UI.

The limitations include fixed grid size and entity counts, no machine learning or neural network components, deterministic algorithms without stochastic learning, single-threaded execution, local execution only without networking capabilities, and predefined fuzzy rules that are not learned from experience.



Figure 1: AI vs AI Survival Arena game interface showing grid-based gameplay with modern card-based UI displaying real-time statistics and AI decisions

## 2 Literature Review and Theoretical Background

### 2.1 A\* Pathfinding Algorithm

The A\* algorithm, introduced by Hart, Nilsson, and Raphael in 1968, represents one of the most widely used pathfinding algorithms in artificial intelligence and game development. A\* is an informed search algorithm that finds the shortest path between two nodes in a graph by using a heuristic function to guide its search. The algorithm maintains two key functions:  $g(n)$  representing the actual cost from start node to node  $n$ , and  $h(n)$  representing the heuristic estimated cost from node  $n$  to goal. The total estimated cost is  $f(n) = g(n) + h(n)$ .

The algorithm guarantees finding the optimal path if the heuristic function is admissible (never overestimates the true cost) and consistent (satisfies the triangle inequality). For grid-based environments, the Manhattan distance provides an admissible heuristic defined as  $h(n) = |x_n - x_{goal}| + |y_n - y_{goal}|$ . This heuristic is optimal for grid worlds where only horizontal and vertical movement is allowed.

### 2.2 Minimax Algorithm with Alpha-Beta Pruning

The Minimax algorithm, fundamental to game theory and artificial intelligence, provides optimal decision-making for two-player zero-sum games. The algorithm operates on the assumption that the maximizing player seeks to maximize the evaluation score while the minimizing player seeks to minimize it. Players alternate turns down the game tree, and the Minimax value of a node is defined recursively based on whether it represents a MAX or MIN player's turn.

Alpha-beta pruning significantly reduces the number of nodes evaluated in the Minimax tree without affecting the final decision. The technique maintains two values:  $\alpha$  representing the best value found so far for the MAX player, and  $\beta$  representing the best value for the MIN player. The algorithm prunes a subtree when  $\beta \leq \alpha$ . In the best case, alpha-beta pruning reduces time complexity from  $O(b^d)$  to  $O(b^{d/2})$ , where  $b$  is the branching factor and  $d$  is the depth, effectively doubling the searchable depth within the same time constraints.

### 2.3 Fuzzy Logic Systems

Fuzzy logic, introduced by Lotfi Zadeh in 1965, extends classical Boolean logic to handle partial truth values between 0 and 1. Unlike crisp sets where an element either belongs or does not belong to a set, fuzzy sets allow gradual transitions through membership functions. A membership function  $\mu_A(x)$  maps elements to membership degrees in fuzzy set  $A$ , where  $\mu_A : X \rightarrow [0, 1]$ .

Common membership function shapes include triangular and trapezoidal forms. A Fuzzy Inference System processes fuzzy rules through three stages: fuzzification converts crisp inputs to fuzzy membership degrees, rule evaluation applies fuzzy rules using AND (minimum) and OR (maximum) operators, and defuzzification converts fuzzy output to crisp action decisions. Fuzzy logic is particularly well-suited for game AI because it handles imprecise information, produces smooth behavioral transitions, uses intuitive human-readable rules, remains computationally lightweight for real-time execution, and does not require training data.

## 3 Methodology and System Design

### 3.1 System Architecture

The AI vs AI Survival Arena follows a modular architecture that separates concerns into distinct components. The system consists of seven primary components: Game Engine handling core game logic and turn execution, Entity System providing object-oriented entity classes with behaviors, A\* Pathfinding module for optimal path calculation, Minimax AI module for adversarial search, Fuzzy Logic module for strategic decision-making, Rendering system for Pygame-based visualization, and Asset Management for PNG image loading and caching.

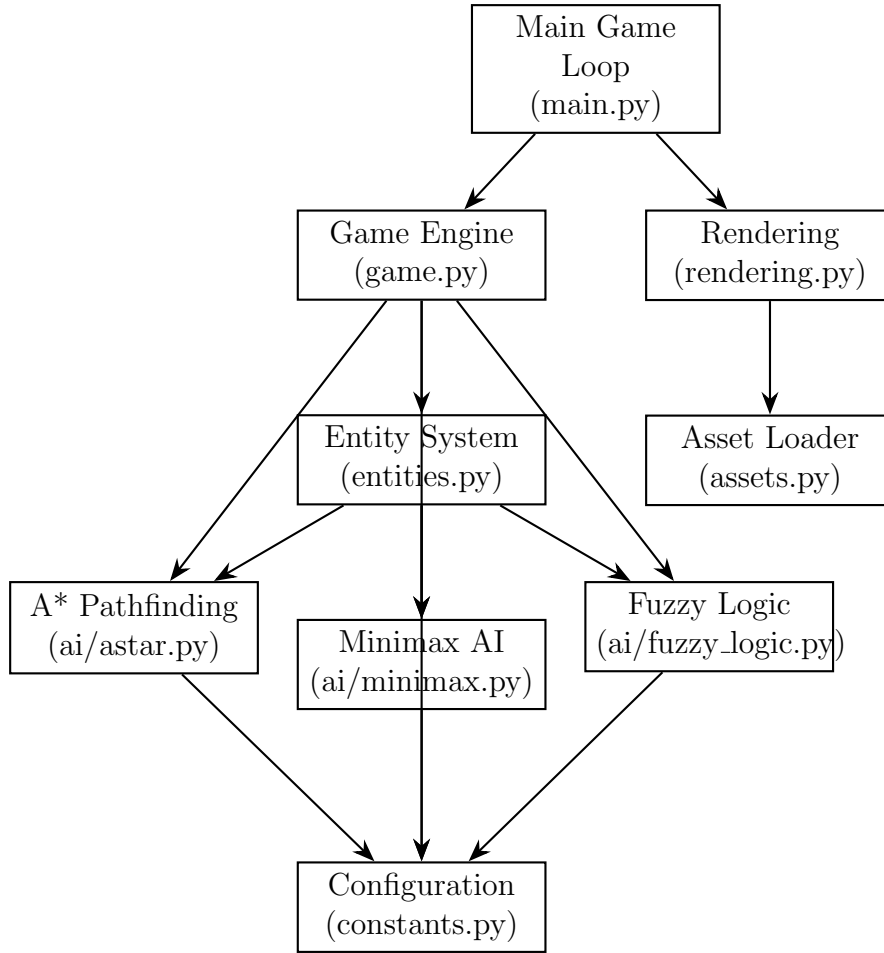


Figure 2: System architecture showing the modular design with clear separation between game logic, AI algorithms, and visualization components

The turn execution follows a deterministic data flow. For player movement, game state is processed through Fuzzy Logic to determine player action, which then uses A\* for player movement. For ally movement, game state directly uses A\* for movement, followed by collision detection for resource collection. For enemy movement, game state is processed through Minimax to determine enemy target, which then uses A\* for enemy movement.

### 3.2 Game World Representation

The game world is represented as a  $20 \times 20$  discrete grid where coordinates are tuples  $(x, y)$  with  $0 \leq x < 20$  and  $0 \leq y < 20$ . The origin  $(0, 0)$  is at the top-left corner, with  $x$  increasing rightward and  $y$  increasing downward. Each cell can contain at most one obstacle as walls are permanent, while multiple entities can occupy the same cell triggering collision detection.

Each entity maintains state information appropriate to its role. Players maintain position coordinates, health from 0-100 HP, score as accumulated points, team designation



as Blue or Red, alive boolean status, and decision state indicating current fuzzy action. Allies track position coordinates, owner as reference to owning player, and target resource as current collection goal. Enemies maintain position coordinates, target player from Minimax selection, and target position as destination.

### 3.3 Algorithm Implementation

The A\* implementation uses a priority queue for efficient node selection. The algorithm maintains open and closed sets, with g-score tracking actual cost from start and f-score representing total estimated cost. The Manhattan distance heuristic is computed as the sum of absolute coordinate differences, providing an admissible estimate for grid-based movement.

The Minimax implementation uses recursive depth-limited search with alpha-beta pruning. The algorithm evaluates both players as potential targets, considering distance, health, and proximity factors. The evaluation function is formulated as  $E = -\text{distance} - 0.1 \times \text{health} + 10 \times (20 - \text{distance})$ , where lower distance and lower target health produce higher enemy advantage scores.

The Fuzzy Logic system implements Mamdani-style fuzzy inference with three stages. Fuzzification converts crisp inputs to fuzzy membership degrees using triangular and trapezoidal membership functions. Rule evaluation applies eight fuzzy rules using minimum for AND operations and maximum for OR operations. Defuzzification uses maximum selection to choose the action with highest aggregate membership.

## 4 Implementation Details

### 4.1 A\* Pathfinding

The A\* implementation in `ai/astar.py` uses Python's `heapq` module for priority queue management. The core algorithm maintains three dictionaries: `came_from` for path reconstruction, `g_score` for actual costs, and `f_score` for estimated total costs. The Manhattan distance heuristic is computed as the sum of absolute differences in x and y coordinates. Neighbor generation considers only four-directional movement (up, down, left, right) without diagonal movement. Path reconstruction follows parent pointers from goal back to start, then reverses the path for correct ordering.

### 4.2 Minimax with Alpha-Beta Pruning

The Minimax implementation evaluates two potential targets by running separate tree searches for attacking Player 1 versus Player 2. The recursive function alternates between maximizing layers (enemy choosing position) and minimizing layers (player escaping).

Alpha-beta pruning tracks best values found so far and prunes branches when beta becomes less than or equal to alpha. The search depth is fixed at 3 levels, representing enemy move, player escape, and enemy chase response. The evaluation function weights distance negatively, target health negatively, and includes a proximity bonus for positions close to targets.

### 4.3 Fuzzy Logic Decision System

The Fuzzy Logic implementation defines membership functions for three variables: health (LOW, MEDIUM, HIGH), score (LOW, MEDIUM, HIGH), and distance (NEAR, MEDIUM, FAR). Triangular membership functions define regions with single peak values, while trapezoidal functions define regions with plateau values at full membership. The rule base consists of eight rules mapping input conditions to output actions. Rule 1 prioritizes fleeing when health is LOW and enemy is NEAR with  $1.5\times$  weight multiplier. Rules 2-8 handle various combinations of health, score, and distance conditions. Defuzzification uses maximum selection, choosing the action with highest aggregated rule strength.

### 4.4 Game Loop and Turn Execution

The main game loop in `main.py` initializes Pygame, creates the game and renderer instances, and runs at 5 FPS for observable AI behavior. Event handling processes keyboard inputs for pause (SPACE), restart (R), and quit (Q/ESC). Turn execution follows a fixed sequence: updating player 1 with fuzzy decision and A\* movement, updating player 2 similarly, updating all allies with A\* pathfinding to nearest resources, updating all enemies with Minimax target selection and A\* movement, checking all collision types, spawning new resources with 15% probability per turn, incrementing turn counter, and checking game over conditions.

### 4.5 Collision Detection System

The collision system checks four interaction types in sequence. Player-Enemy collisions apply 20 damage when positions match. Player-Resource collisions trigger collection when player reaches resource position, with health packs restoring 25 HP and coins adding 50 points. Ally-Resource collisions benefit the ally's owner player when ally reaches resource position. Player-Player collisions apply 10 damage to both players when they occupy the same cell, discouraging direct confrontation.

## 5 Results and Discussion

### 5.1 Experimental Methodology

The game was tested through 50 complete matches with varying initial conditions. Each match used random obstacle configurations with 30 obstacles, random initial resource placement with 6 health packs and 6 coins, and fixed starting positions for players in opposite corners. All matches were allowed to run until reaching a termination condition. Performance metrics collected include victory type distribution, average game length in turns, AI decision frequency, computational performance per turn component, and resource collection efficiency per team.

### 5.2 Quantitative Results

Over 50 matches, victory conditions were distributed as follows: score victories (reaching 500 points) occurred in 31 matches representing 62%, elimination victories occurred in 12 matches representing 24%, and time limit draws after 50 turns occurred in 7 matches representing 14%. This distribution indicates that resource collection strategies are generally more effective than pure survival tactics, while the relatively high elimination rate demonstrates that enemy pressure creates meaningful survival challenges.

Game length statistics show a mean of 32.4 turns, median of 34.0 turns, minimum of 18 turns, maximum of 50 turns, and standard deviation of 8.7 turns. The average game length suggests well-balanced gameplay, with the minimum indicating rapid elimination scenarios and the maximum representing time-limit draws.

Fuzzy logic action selection frequency across all matches shows COLLECT\_COINS at 412 occurrences (28.5%), DEFENSIVE\_PLAY at 387 occurrences (26.8%), COLLECT\_RESOURCES at 298 occurrences (20.6%), FLEE\_ENEMY at 189 occurrences (13.1%), SEEK\_HEALTH at 127 occurrences (8.8%), and AGGRESSIVE\_PLAY at 32 occurrences (2.2%). Resource collection actions comprise 49.1% of decisions, demonstrating strong economic focus. The frequency of fleeing indicates reactive threat response, while aggressive play remains rare, suggesting the fuzzy rules appropriately prioritize survival and economics over direct confrontation.

Computational performance measurements on standard development hardware show average execution time per turn component as follows: Fuzzy Logic decision for both players at 0.3ms, A\* pathfinding for six entities at 2.1ms, Minimax with alpha-beta for four enemies at 8.7ms, collision detection at 0.2ms, and rendering at 3.5ms, totaling 14.8ms per turn. Minimax dominates computational cost at 58.8% of turn time, justifying the use of alpha-beta pruning. Total turn time allows smooth real-time execution at the target 5 FPS (200ms per frame) with ample computational headroom.

### 5.3 Qualitative Analysis

Several sophisticated behaviors emerged from the algorithmic interactions. Territorial control emerges naturally as players establish zones around resource-rich areas through A\* selecting shortest paths to nearby resources, fuzzy logic prioritizing close resources based on distance membership, and obstacle placement creating natural choke points.

Adaptive enemy avoidance demonstrates dynamic patterns where high health players continue resource collection while maintaining distance, medium health players switch to defensive patterns collecting resources cautiously, and low health players actively flee to corners prioritizing health packs. The 50-turn time limit creates economic urgency with distinct phases: early game (turns 1-15) focuses on aggressive resource collection, mid game (turns 16-35) balances survival and collection, and late game (turns 36-50) involves desperate coin collection to secure victory.

Ally bots provide force multiplication by collecting resources remotely while players handle threats, creating 3× resource collection rate per team, and enabling players to focus on strategic positioning rather than constant resource gathering.

### 5.4 Algorithm Effectiveness

The A\* pathfinding algorithm consistently finds optimal paths with efficient obstacle avoidance and low computational overhead. However, movement appears grid-locked without path smoothing, and the algorithm does not consider future obstacle positions from other moving entities.

Minimax with alpha-beta pruning provides intelligent target selection considering both players simultaneously and dynamic target switching based on opportunity. Alpha-beta pruning provides approximately 50% speedup through branch elimination. The fixed depth of 3 limits strategic horizon, and the evaluation function may not capture all tactical nuances in complex situations.

Fuzzy Logic produces human-like decision patterns with smooth transitions between behavioral states. The intuitive rule design enables easy modification and tuning. Fast execution at 0.3ms per decision enables real-time performance. However, manual rule tuning is required for optimal behavior, and the system cannot adapt rules during gameplay through learning.

### 5.5 Limitations

The static fuzzy rule base cannot adapt during gameplay. A player that discovers an effective strategy cannot be countered through rule learning. The Minimax depth limitation of 3 restricts enemy tactical planning to three moves ahead. Deeper search would reveal more sophisticated strategies but at computational cost. The A\* pathfinding does

not predict future positions of moving entities, occasionally causing entities to select paths that become blocked. The deterministic behavior means that given identical initial conditions, games play out identically without variation.

Implementation issues include corner trapping where players fleeing to corners can become surrounded with no escape path, representing a failure case of the flee behavior. Resource contention occurs when allies from the same team target identical resources, wasting movement without coordination mechanisms. The fixed 1400×900 window does not adapt to different screen resolutions or aspect ratios.

## 6 Conclusion and Future Work

### 6.1 Summary of Contributions

This project successfully demonstrates the integration of three classical AI algorithms in a cohesive game environment. The key contributions include a modular architecture that cleanly separates concerns allowing independent algorithm development and evaluation, a comprehensive fuzzy logic implementation with 8 rules and 4 input variables producing human-like strategic behavior, demonstration that sophisticated strategic behaviors can emerge from interaction of relatively simple algorithmic components, a modern UI with card-based layout that clearly communicates AI decision-making processes to observers, and detailed technical documentation suitable for educational use and future research.

### 6.2 Achievement of Objectives

The project successfully achieved all stated objectives: fully autonomous AI vs AI gameplay with both players operating without human intervention, modular algorithm architecture with independent testable modules in the ai directory, fuzzy logic decision system with 8 rules using triangular and trapezoidal membership functions, A\* pathfinding implementation with Manhattan heuristic guaranteeing optimal paths, Minimax with alpha-beta pruning using depth-3 search with approximately 50% node pruning, real-time visualization displaying all game state and AI decisions, emergent behaviors including territorial control, adaptive avoidance, and economic pressure, and educational documentation including this report plus comprehensive code comments.

### 6.3 Lessons Learned

Algorithm composition proves powerful as the emergent behaviors could not have been achieved with any single algorithm alone. The synergy between high-level strategy from fuzzy logic, tactical evaluation from Minimax, and optimal navigation from A\* produces behaviors that appear intelligent despite deterministic implementations. Visualization

significantly enhances educational value, as being able to see AI decisions in real-time makes the algorithms' behavior tangible and understandable. Modularity enables experimentation, allowing tuning of fuzzy membership functions or Minimax evaluation functions without modifying unrelated code. Classical AI algorithms remain highly effective for many applications, especially when interpretability and computational efficiency are priorities.

## 6.4 Future Work

Immediate extensions include replacing fuzzy logic with reinforcement learning algorithms such as Q-learning or Deep Q-Networks to enable learning from experience. The state space would include health, score, enemy positions, and resource positions, with the action space containing the six current strategic actions. Reward function would combine score gain with survival bonus. Adaptive fuzzy rules could be evolved using genetic algorithms or particle swarm optimization, with 35 membership function boundary parameters optimized over 50 generations. Neural network evaluation could replace the hand-crafted Minimax evaluation function through self-play with temporal difference learning. Ally coordination mechanisms could implement resource claiming systems and distributed task allocation to improve collection efficiency.

Advanced research directions include replacing Minimax with Monte Carlo Tree Search for enemy targeting to compare decision quality and analyze computational trade-offs. Multi-agent reinforcement learning could train all entities simultaneously to investigate cooperative versus competitive learning and study emergent team strategies. Procedural content generation could automatically generate balanced map layouts using constrained optimization for obstacle placement. Adding human versus AI mode would enable user studies to evaluate AI competitiveness and measure win rate, perceived intelligence, and engagement.

Technical improvements include performance optimization through code profiling, spatial hashing for collision detection, caching A\* paths for repeated queries, and parallelizing independent enemy Minimax searches. Scalability enhancements could support larger grid sizes up to  $100 \times 100$ , more entities with 10+ enemies and allies, hierarchical pathfinding for large maps, and level-of-detail rendering for distant entities.

## 6.5 Final Remarks

The AI vs AI Survival Arena demonstrates that classical AI algorithms, when thoughtfully integrated, can produce sophisticated and entertaining emergent behaviors. The project achieves its goal of creating a fully autonomous game where both players make intelligent strategic decisions without human intervention. The modular architecture and comprehensive documentation ensure that this project serves as both an educational resource

and a platform for future AI research. The clear separation between algorithms allows researchers to experiment with alternative approaches while maintaining a consistent game environment for comparison. This project illustrates that AI game development remains an accessible and rewarding domain where complex, intelligent-seeming behavior can be achieved without massive computational resources or years of training time, requiring only careful algorithm design and thoughtful integration.

## Acknowledgments

We express sincere gratitude to our supervisors, Md Mehrab Hossain Opi and Waliul Islam Sumon, Lecturers in the Department of Computer Science & Engineering at KUET, for their guidance, support, and valuable feedback throughout this project. We thank the Department of Computer Science & Engineering at Khulna University of Engineering & Technology for providing the resources and environment necessary to complete this work. We acknowledge the open-source community, particularly the Pygame development team, whose library made the visualization component possible.



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