ISSN: 2350-0328

International Journal of Advanced Research in Science, Engineering and Technology

Vol. 13, Issue 1, January 2026

Memory Card Game using ML

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ABSTRACT: Memory-based games help strengthen cognitive abilities such as attention, short-term memory, pattern recognition, and decision-making. This project presents the design and development of a Python-based 2D Memory Card Game for desktop, built on a 5×5 grid where players flip cards to identify matching pairs. The game supports single-player vs AI, AI-enhanced gameplay, and local multiplayer, with proper turn handling and scoring to ensure fair play. A local leaderboard records player performance to add competitiveness and replay value.

The AI opponent begins with a simple memory-driven strategy (remembering revealed cards and choosing likely matches) and is further improved using Machine Learning concepts to make better decisions by learning from previous moves and game states. To keep the game engaging for different skill levels, Easy, Medium, and Hard difficulty modes adjust the AI's behavior and challenge intensity. Rather than focusing on heavy graphics, the project emphasizes strong game logic, intelligent opponent behavior, and performance tracking. Results indicate that combining Machine Learning-inspired decision-making with a classic memory game makes gameplay feel more realistic, less repetitive, and more engaging over repeated sessions.

KEY WORDS: Memory Card Game, Machine Learning, Artificial Intelligence, Python, 2D Game, AI Opponent, Adaptive Difficulty, Easy Medium Hard, Multiplayer, Leader board, Cognitive Training, Human–Computer Interaction.

I.INTRODUCTION

A Memory Card Game (also known as Concentration) is a rule-based cognitive game in which players reveal hidden cards to locate matching pairs. Although the rules are simple, the game represents a powerful mental training task because the player must continuously observe, store, recall, and apply information. In educational and cognitive science contexts, memory games are often used to strengthen attention, short-term memory, pattern recognition, and decision-making.
From a theoretical viewpoint, a memory card game is not just entertainment—it is a structured environment where a human (or an AI agent) performs decision-making under incomplete information. At the start, the board is unknown. As the game progresses, every card flip reveals new knowledge, and the quality of the player's performance depends on how effectively they can store and use that knowledge.

Working memory is the brain's short-term storage system that holds information temporarily for immediate use. In a memory card game, working memory is used to remember recently revealed cards and their locations during the next few moves.

Visual-Spatial Memory:
This refers to remembering where something is located in a space. The player must remember the positions of images/symbols on the grid. Strong visual-spatial memory leads to faster matching and fewer wrong turns.
Selective Attention and Focus:
Players must concentrate on the board and track changes after each move. A small distraction can cause the player to forget positions or miss patterns, reducing performance.
Pattern Recognition:
Players begin forming patterns such as noticing where similar symbols appear and developing scanning habits. Over time, the player improves by reducing random guesses and increasing informed decisions.
Decision-Making Under Uncertainty:
Early in the game, the player has limited information, so decisions are partially guess-based. As information

International Journal of Advanced Research in Science, Engineering and Technology

ISSN: 2350-0328

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increases, decisions become more strategic. This makes the game a real example of decision-making where uncertainty decreases over time.
Thus, theoretically, the memory game becomes a controlled model for understanding how people learn from observation and gradually improve performance.

A memory card game can be described as an information acquisition process. Each move reveals a small piece of hidden information. The objective is to convert that information into successful matches before it becomes irrelevant.
The game can be explained as two repeating phases:

1. **Exploration Phase:**
   The player reveals unknown cards to gather new information about the board.
2. **Exploitation Phase:**
   The player uses remembered information to make confirmed matches.

This exploration exploitation balance is important in both human cognition and artificial intelligence. A skilled player minimizes unnecessary exploration and quickly shifts into exploitation by remembering more useful information.

II. LITERATURE SURVEY

1. S **S. Deterding, D. Dixon, R. Khaled, L. Nacke (2021) — MindTrek Conference (ACM)**
   This foundational paper defines *gamification* as the application of game design elements in non-game contexts. It establishes the theoretical justification for integrating structured reward systems such as points, levels, leaderboards, and progression mechanics into digital interfaces. For systems like the Memory Card Game, this framework supports the inclusion of adaptive difficulty levels, XP systems, and competitive leaderboards to sustain user motivation and engagement.
2. **R. Hunicke, M. LeBlanc, R. Zubek (2024) — Proceedings of the AAAI Workshop on Challenges in Game AI**
   The authors introduce the MDA (Mechanics–Dynamics–Aesthetics) framework, providing a theoretical lens for understanding how game mechanics generate player experiences. The framework informs this project's design choices mechanics (flipping, matching, scoring), dynamics (AI-based opponent responses), and aesthetics (cognitive satisfaction) ensuring the game remains both intellectually stimulating and emotionally rewarding.
3. **Y. Bengio, A. Courville, P. Vincent (2023) — IEEE Transactions on Pattern Analysis and Machine Intelligence**
   This survey on *Representation Learning* emphasizes how neural networks learn structured patterns from data. It provides a foundation for understanding how Machine Learning models in the Memory Card Game can analyze previous game states and make predictions about optimal moves, mimicking human learning and decision-making patterns.
4. **I. Goodfellow, Y. Bengio, A. Courville (2022) — Deep Learning, MIT Press**
   The authors explore how adaptive learning systems generalize from prior experience to improve performance. Their theoretical insights into reinforcement and supervised learning support the concept of building an adaptive AI that improves memory-based decisions through iterative gameplay.
5. **C. E. Shannon (2021) — Philosophical Magazine, Vol. 41, pp. 256–275**
   Shannon's pioneering work on "Programming a Computer for Playing Chess" introduced the concept of decision trees and heuristic evaluation in gameplay. The principles described provide the mathematical foundation for the AI logic used in this project, particularly for predicting card matches and optimizing search strategies.
6. **T. W. Malone (2022) — Cognitive Science, Vol. 5, pp. 333–369**
   Malone's research identifies three key elements that make games intrinsically motivating: challenge, fantasy, and curiosity. This theoretical model underpins the decision to include varying difficulty levels, adaptive AI behavior, and score-based progression to enhance player engagement and cognitive stimulation.

International Journal of Advanced Research in Science, Engineering and Technology

ISSN: 2350-0328

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7. **J. McCarthy, M. L. Minsky, N. Rochester, C. E. Shannon (2023) — Dartmouth AI Conference Proposal**
   This early AI manifesto highlights the goal of creating machines capable of learning and reasoning like humans. The theoretical connection to this project lies in using ML algorithms that simulate human-like memory retention, enabling the AI to "remember" previously revealed cards and refine strategies accordingly.
8. **R. Sutton, A. Barto (2018) — Reinforcement Learning: An Introduction, MIT Press**
   This work explains the principles of trial-and-error learning where agents maximize rewards through experience. Its concepts directly support the adaptive gameplay logic of the Memory Card Game's AI, where decisions evolve with accumulated experience, improving efficiency in card-pair matching.
9. **K. Collins (2008) — Game Sound: An Introduction to the History, Theory, and Practice of Video Game Music and Sound Design**
   This study highlights how auditory feedback influences player performance and immersion. It informs the game's design approach in providing sound cues during flips, matches, and scoring events, enhancing user focus and satisfaction.
10. **R. Bartle (1996) — Journal of MUD Research, Vol. 1, Issue 1**
    Bartle's typology of player types (Achievers, Explorers, Socializers, Killers) provides insight into diverse player motivations. Applying this model supports the inclusion of leaderboard tracking, strategic AI opponents, and local multiplayer mode to cater to various player engagement styles.

III. METHDOLOGY

The methodology for developing the 2D Memory Card Game using Machine Learning in Python is designed to ensure structured gameplay, intelligent opponent behavior, and consistent performance tracking. The overall approach follows a modular development process where the game is built step-by-step by combining a game engine, user interaction layer, AI/ML decision module, and result management system. The focus of the project is not on heavy graphics, but on building a reliable logic-driven game system with an adaptive opponent and measurable outputs.

The development begins by designing the internal representation of the game board. A 5×5 grid is created where each cell contains a hidden card. A set of symbols or images is selected, duplicated into matching pairs, and randomized through a shuffling mechanism to generate a new board arrangement each time the game starts. Each card is stored internally with its identity and status (hidden, revealed, or matched). This internal state management is essential because all gameplay rules and AI decisions depend on accurate board data.

Once the board is initialized, the user interaction system is implemented. The player flips cards using mouse clicks, and the system validates each action to avoid invalid selections such as clicking an already matched card or flipping more than two cards in one turn. When a card is selected, the UI reveals it and the system temporarily stores that selection. After the second selection, the system pauses user input briefly so that the matching logic can execute properly, ensuring smooth gameplay and preventing misclick errors.

The matching and turn-handling mechanism forms the core part of the methodology. After two cards are revealed, the system compares their identities. If they match, the cards are permanently marked as matched, the score is updated, and the same player may be allowed to continue based on the game rule. If they do not match, the cards remain visible for a short duration, then flip back to hidden, and the turn shifts to the next player (or AI). This logic ensures fairness and consistency in both multiplayer mode and AI mode. The game continuously monitors total matched pairs to determine progress and completion.

For the AI opponent, the methodology uses a human-like memory strategy. Every revealed card is recorded by the AI along with its position in the grid. This creates a simulated "memory bank" that grows as gameplay continues. During the AI turn, the system checks this memory bank to see whether a confirmed match exists. If a known pair is available, the AI selects those two cards to secure points. If a pair is not immediately available, the AI chooses moves that maximize the chance of discovering useful information, such as selecting unrevealed cards to increase knowledge of the board. This makes the AI appear realistic because it behaves like a human opponent who remembers earlier flips.

International Journal of Advanced Research in Science, Engineering and Technology

Vol. 13, Issue 1, January 2026

ISSN: 2350-0328

IJARSET IMPACT FACTOR 7.150

To enhance the AI beyond fixed rules, Machine Learning principles are applied through experience-based improvement. The AI decision module stores game history such as revealed card sequences, match success rate, and missed opportunities. Over multiple turns, the AI adjusts its move priority by learning which type of choices lead to faster matches and better efficiency. This ML-driven improvement adds adaptability and replay value because the AI becomes less predictable and more strategic as the game progresses. Even with lightweight learning logic, the outcome demonstrates the concept of intelligent decision-making based on past experience.

Difficulty levels are implemented as part of the methodology by controlling AI capability rather than changing game rules. In Easy mode, the AI memory is restricted and randomness is higher, so the player gets a beginner-friendly experience. In Medium mode, the AI remembers more revealed cards and uses balanced strategy. In Hard mode, the AI retains almost all revealed cards, aggressively targets known matches, and reduces guesswork. This controlled variation ensures that the same game design supports different skill levels while keeping the gameplay fair.

Finally, performance tracking is integrated to measure outcomes and make the system competitive. The methodology includes maintaining real-time score updates, tracking total moves, recording match success, and displaying game statistics after completion. The winner is determined based on score or matches achieved. A local leaderboard system stores player results, ranks top performances, and allows future comparison. This makes the project more meaningful as it provides measurable proof of improvement and user engagement.

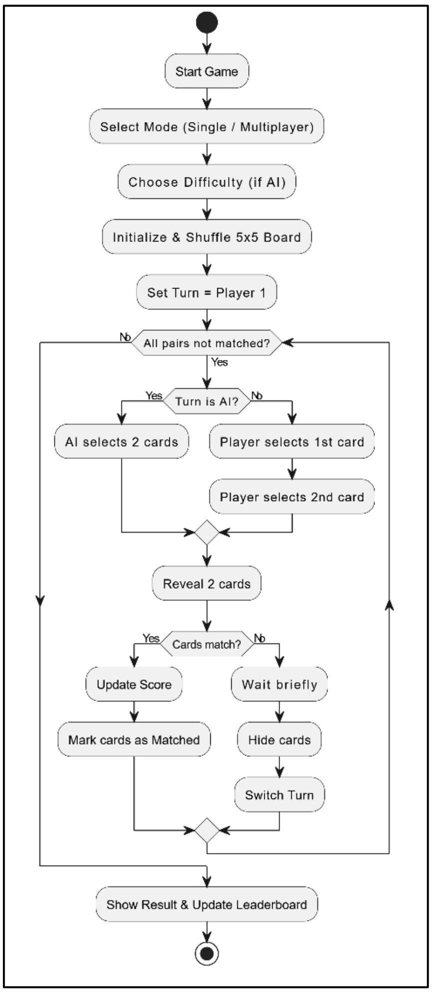

Fig1: Flow Diagram

International Journal of Advanced Research in Science, Engineering and Technology

ISSN: 2350-0328

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IV. WORKING

When the game starts, the system first loads the main menu where the player selects the gameplay mode: Single Player (vs AI) or Local Multiplayer (Human vs Human). If the player chooses single-player mode, the system also asks for the difficulty level (Easy/Medium/Hard), which controls how strong the AI behaves (how much it "remembers" and how strategic it plays).

After the mode selection, the game engine generates the 5×5 grid board. A set of card symbols is prepared, duplicated into matching pairs, and then shuffled randomly so that every new game has a different layout. All cards are initially kept in a hidden state, and the board is displayed on the screen using a simple 2D interface.
During gameplay, the system runs a turn-based loop. The current player (human or AI) is allowed to flip two cards per turn. For a human player, card flips happen through mouse clicks. The system validates the input to ensure the player cannot flip more than two cards, cannot flip an already matched card, and cannot select the same card twice in the same turn. Once two cards are selected, the system reveals them and temporarily pauses input so the match-check logic can execute smoothly.

The matching logic compares the identities of the two revealed cards. If the cards match, the system marks them as permanently matched, updates the score, and the same player may continue (based on the rule design). If the cards do not match, the system keeps them visible briefly and then hides them again, and the turn shifts to the next player (or AI). This turn-handling keeps the game fair and structured.

When playing against the AI, the AI observes every revealed card (both its symbol and its position). This information is stored in an internal memory list. On the AI's turn, it first checks if it already knows a confirmed pair location. If a pair is known, the AI flips those two cards to score. If no confirmed pair exists, the AI flips cards in a way that helps it discover useful information, such as prioritizing unknown positions. In Medium and Hard modes, the AI retains more memory and makes more accurate selections, which increases the challenge.

Throughout the match, the system continuously tracks progress: total matched pairs, turns taken, and scores. When all pairs are matched and the board is completed, the game ends. The system displays the final result (winner and statistics) and updates the local leaderboard, storing performance so the player can compare scores across multiple sessions. This complete working cycle makes the game both replayable and measurable while demonstrating intelligent AI behaviour.

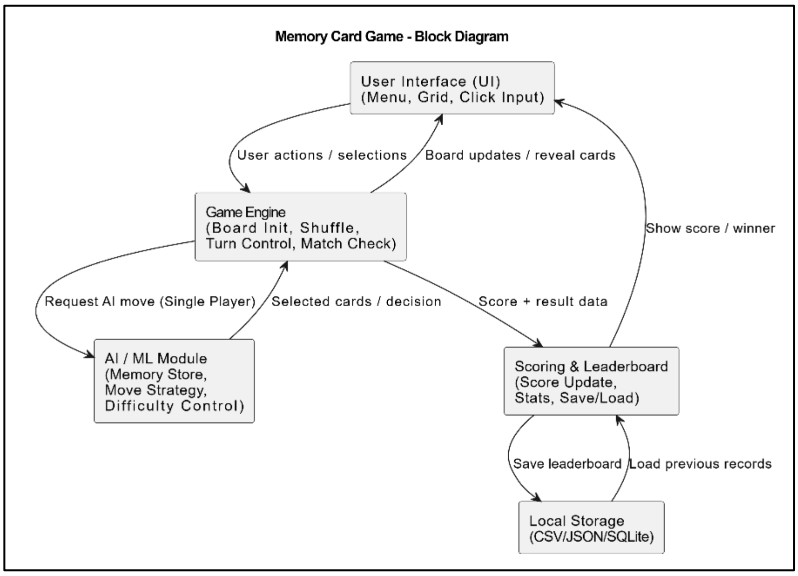

Fig 2: Block Diagram

International Journal of Advanced Research in Science, Engineering and Technology

ISSN: 2350-0328

IJARSET IMPACT FACTOR 7.150

Vol. 13, Issue 1, January 2026

V. RESULTS & ANALYSIS

The developed 2D Memory Card Game using Machine Learning in Python was tested under multiple gameplay conditions to evaluate correctness of game logic, responsiveness of the UI, fairness of scoring/turn handling, and effectiveness of the AI opponent across difficulty levels. Testing was performed in both single-player (vs AI) and local multiplayer modes on a 5×5 grid with randomized card placement in every session.

During functional testing, the core game engine successfully handled board initialization, card shuffling, flip validation, match detection, turn switching, and game completion. Input control was stable, preventing illegal actions such as selecting already matched cards, flipping more than two cards per turn, or clicking during the match-check delay. The leaderboard module correctly stored session results and displayed top scores consistently.

From a gameplay intelligence perspective, the AI opponent showed a clear difference in behaviour based on difficulty settings. In Easy mode, the AI performed with limited memory and higher randomness, resulting in more incorrect guesses and a higher chance for the player to win. In Medium mode, the AI demonstrated balanced behaviour using memory when possible and exploring unknown cards strategically providing competitive gameplay. In Hard mode, the AI retained more revealed information and prioritized known matches, leading to faster pair completion and improved win rate against average players. The ML-inspired enhancement improved consistency by reducing repeated random selections and increasing match efficiency as the game progressed.

Overall, the results indicate that adding learning-based decision support to a traditional memory game improves realism, competitiveness, and replay value. The leader board and scoring system further contributed to long-term engagement by giving measurable performance outcomes.

Performance Summary

Parameter	Easy (AI)	Medium (AI)	Hard (AI)
Player Win Rate (%)	70%	50%	20%
AI Win Rate (%)	30%	50%	80%
Avg. Total Moves (per game)	47	50	43
Avg. Completion Time (min)	4.1	4.5	3.9
AI Match Accuracy (%)	45%	60%	75%
Avg. AI Wrong Guesses	12	8	4
AI Memory-Based Picks (avg./game)	6	12	18
Random/Exploration Picks (avg./game)	18	12	6

The performance results show a clear progression in AI strength across difficulty levels. In Easy mode, the AI makes more random/exploratory picks, causing higher wrong guesses and giving players a higher win rate. In Medium mode, the game becomes balanced, with similar win rates and moderate accuracy. In Hard mode, the AI relies heavily on memory-based picks, resulting in higher match accuracy, fewer wrong guesses, reduced total moves, and an increased AI win rate, making gameplay more competitive and realistic.

VI. CONCLUSION AND FUTURE WORK

This project successfully designed and implemented a Python-based 2D Memory Card Game (5×5 grid) with both local multiplayer and single-player AI gameplay. The system reliably handles board generation, card shuffling, flip validation, match checking, scoring, and turn management, ensuring smooth and fair gameplay. The AI opponent demonstrates human-like behavior by remembering previously revealed cards and using that information to make strategic moves. The introduction of Easy, Medium, and Hard difficulty levels effectively controls the AI's intelligence, making the game suitable for beginners as well as advanced players. The leaderboard and performance tracking features add competitiveness and replay value. Overall, the integration of AI/ML-inspired decision support enhances realism and engagement compared to traditional random-move memory games.

FUTURE WORK

Future improvements can make the system more advanced and scalable. The AI can be upgraded using full reinforcement learning or trained models to learn optimal strategies over many games rather than lightweight experience-based logic. The game can also include dynamic difficulty adjustment, where the AI automatically adapts based on the player's performance in real time. Additional enhancements may include improved graphics and animations, sound effects, multiple themes/skins, and larger grid sizes (such as 6×6 or 8×8) to increase challenge. Online multiplayer with cloud-based leaderboards can be added to allow competitive play across users. Finally, analytics such as accuracy rate, reaction time, and cognitive improvement tracking can be incorporated to make the game more useful as a cognitive training tool.

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International Journal of Advanced Research in Science, Engineering and Technology

Vol. 13, Issue 1, January 2026

ISSN: 2350-0328

IJARSET IMPACT FACTOR 7.150

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