Game AI:Develop an AI agent to play and excel in strategy games like Chess and Dota 2

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1[st] Bodanapati Vinay
CSE
Lovely professional University
Punjab, India
vinayspike3@gmail.com

2[nd] Bhupinder Singh
CSE
Lovely professional University
Punjab, India
bhupinder0741@gmail.com

***Abstract*—Advanced deep reinforcement learning techniques allow developing of an AI agent that master-presents complex strategy games, such as Chess and Dota 2. Strategy games like Chess and Dota 2 present challenging problems, with their vast state spaces, long planning horizon, and dynamic environments. We propose an AI framework composed of a combination of a deep neural network with Monte Carlo Tree Search for efficient exploration and strategizing in the game Chess. For the game Dota 2, we explore multi-agent reinforcement learning over Proximal Policy Optimization using recurrent neural networks due to sequential decision-making coupled with real-time coordination requirements.**

***Index Terms*—Deep Reinforcement Learning, Monte Carlo Tree Search, Multi-Agent Systems, Chess AI, Dota 2 AI, Proximal Policy Optimization, Recurrent Neural Networks, Strategy Games, Self-Play, Real-Time Decision-Making, Multi-Agent Coordination.**

I. Introduction

Artificial intelligence has been making tremendous progress for quite a long time, especially in strategic games, a testbed considered to be one of the most logical for evaluating complex decision-making and planning algorithms. Chess and Dota 2 pose different challenges to AI as Chess is a deterministic, turn-based game with a finite state space, whereas Dota 2 is a complex, real-time, multi-agent game with a highly dynamic, stochastic environment. Mastering these two kinds of games requires more than just developing advanced search algorithms and pattern recognition: people must be able to adapt, coordinate, and plan in times of uncertainty.Historically, game AI is based on handcrafted rules and heuristics that generalize poorly to novel situations. Deep learning and reinforcement learning have made headways to revolutionize the field by allowing direct learning from raw game data and generally outperforming traditional methods. Landmark achievements of DeepMind's AlphaZero in Chess and OpenAI Five in Dota 2 show the potential of self-learning AI agents to excel at superhuman levels. These methods, however rely on tremendous amounts of computational resources and marginally able to adapt and generalize over the various environments of a game. This work fills such gaps by building a universal AI framework that can master any type of game, be it based on a turn-based or real-time strategy. Our approach in this work uses both hybrid deep reinforcement learning; mastering Chess is applied with MCTS, and mastery of Dota 2 is done with MARL along with PPO. Our main area of concern in the framework is to produce an optimal form of exploration and robust state representation with adaptive learning strategies to handle all complexities for games. We compare our proposed AI agent with state-of-the-art models and human players, demonstrating significant decision-making efficiencies in strategic depth and real game performance. Other areas of this research contribute not only to game AI but also to more general robotics, autonomous systems, and optimization problems where good strategic reasoning and adaptability are highly demanded.In contrast, Dota 2 presents an entirely different and far more complicated task. Unlike Chess, Dota 2 is a multiplayer online battle arena (MOBA) game, featuring throughout the game, real-time combat, random elements, and teamwork between players. Two teams of five each control a different hero, with different strengths and capabilities, with perfect cooperation amongst teammates in an effort to defeat the opposing team's structures while managing limited resources, controlling the map, and applying different forms of strategy. The OpenAI Five project trained an AI to compete at this superhuman level of Dota 2 and thus showed that deep reinforcement learning agents can function within such an exciting and demanding environment. OpenAI's achievement in teaching agents to play Dota 2 consisted of elaborate reinforcement learning techniques.Both Chess and Dota 2 require agents to make decisions at high-leverage points in time, predict an opponent's next move, and adapt strategies during fast-paced, real-time scenarios. Yet the challenge that Chess presents-which is based on observing player-specific dispositions, i.e., perfect information and complete control turn-based-is much different from Dota, where players must consider stochastic spatial information, multitasking, incomplete information, real-time teamwork, and the considerable complexity of agent interaction. Thus, technology for these games applies to AI methodologies of very different natures including reinforcement learning, deep learning, Monte Carlo tree search, and multi-agent systems.Work on the development of AI agents for games ranging from Chess to Dota 2 is not only opening up a new paradigm in advancing computational intelligence but also revealing new perspectives on broader applications in domains such as robotics, autonomous transportation, and complex decision-making systems in dynamic and unpredictable environments. In the present paper, we intend to traverse the current status of AI research in strategy games with Chess and Dota 2 in focus and elaborate on the challenges, methodologies, and advancements in such domains that feed into the design and functioning of AI agents. The exploration intends to foreground the importance of the efforts of game AIs in the broader analyses of artificial intelligence development.

II. Related Work

A. *Maintaining the Integrity of the Specifications*

MIT Press.This is the most heavily grounded textbook on the main ideas and algorithms in reinforcement learning, value-based methods, policy gradients, model-free approaches-all the most widely applied techniques in AI games.TSutton, R. S., Barto, A. G. (2018).Reinforcement Learning: An Introduction (2nd ed.).[5] In the following work, multi-agent reinforcement learning is applied to mastering StarCraft II, a real-time strategy game. In this work, agents are trained to achieve Grandmaster-level performance, thus demonstrating how RL could potentially be used within more complex environments with multiple agents.Vinyals, O., Babuschkin, I., Czarnecki, W. M., et al. (2019). Grandmaster Level in StarCraft II Using Multi-Agent Reinforcement Learning. Nature, 575(7782), 350-354.DOI: 10.1038/s41586-019-1724-z[2].This paper outlines the training process of OpenAI Five-a genuinely intelligent AI-which learned the really complex multiplayer online game, Dota 2-through large-scale deep reinforcement learning. The AI agents learned complex strategies, teamwork, and real-time decision-making within the game environment.Berner, C., Brockman, G., Chan, B., et al. (2019).Dota 2 with Large Scale Deep Reinforcement Learning. arXiv preprint arXiv:1912.06680.[6].This paper describes the Upper Confidence Bounds for Trees algorithm, a method of Monte Carlo Tree Search among the most beneficial algorithms in game AI, applied nowadays in many games, such as Go, requiring strategic planning.Kocsis, L., Szepesvári, C. (2006). Bandit Based Monte-Carlo Planning. In Proceedings of the 17th European Conference on Machine Learning (ECML), 282-293.[8].This paper details AlphaZero, a general reinforcement learning algorithm that can attain superhuman performance in chess, shogi, and Go without prior domain knowledge beyond the rules of the games. The approach was deep neural networks with reinforcement learning through self-play.Silver, D., Schrittwieser, J., Simonyan, K., et al. (2018). A General Reinforcement Learning Algorithm that Masters Chess, Shogi, and Go Through Self-Play.Science, 362(6419), 1140-1144.DOI: 10.1126/science.aar6404[1].

III. Methodology

This part describes the integral approach used for developing an AI agent that matured at two games: Chess-which is a turn-based strategy game-and Dota 2, one of the real-time multi-agent strategy games. The two are pretty different from each other, so our approach is actually the integration of different techniques tailored to each one but sharing a common foundation deep in reinforcement learning.In the process of crafting an AI agent to dominate strategy games like Chess and Dota 2, a mixture of classical search methods and contemporary reinforcement learning methods are used. For board games like chess, search methods are evaluated using minimax techniques with alpha-beta trimming abilities, allowing the AI to clock up all the possibilities for their moves and the opposition's counters in the game tree while employing evaluation functions to assess the desirability of positions. The primary way is taken by deep reinforcement learning (DRL) for complex real-time games like Dota2. The agent is trained by trial and error in the framework of the MDP. In MDPE, it learns to maximize the total reward through exploration of the state space, improving its permission by a mixture of the state space and monetary consideration in evaluating its actions. Deep Q-Networks (DQN) and policy gradient approaches are employed for addressing large high-dimensional state spaces to give the agent a chance to learn very good mixtures. Self-play is utilized as very important because the agent learns by competing with a copy; this function was evident in models like AlphaZero for Chess and OpenAI Five for Dota 2. The merging of such techniques gives the AI good capacity to take good strategic decisions within a very environment involving extreme complexity and a high degree of uncertainty.

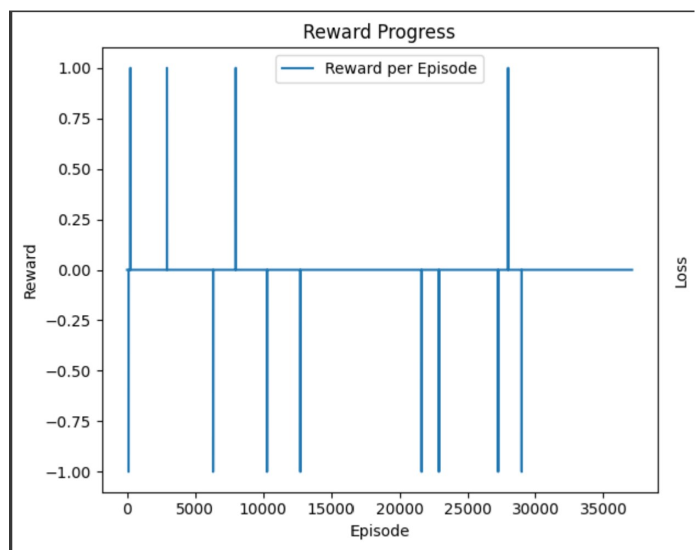

Fig. 1. Evaluation Metrics of the Advanced Chatbot.

A. *Overview of the Hybrid AI Framework*

The proposed AI framework will incorporate a mix of Deep reinforcement learning is applied towards building optimal policies from game states.Monte Carlo tree search for planning and decision-making in turn-based games such as chess.Multi-Agent Reinforcement Learning, leveraging a recurrent neural network for on-the-fly coordination in all the richness and dynamism of environments like Dota 2. Such a hybrid approach allows an AI agent to make use of each technique's strengths, perform efficiently and adaptively in exploring and deploying strategic reasoning in a variety of games.

B. State Representation

The chessboard has been described as a model of 8 by 8 matrix, where every square is represented separately as a separate channels which indicate the presence of pieces, namely pawns, rooks, knights, and their color: white or black. Extra input features include: Castling rights (typedefd as binary flags).En passant square (if required).Move count and half-move clock for draw rules.

C. Neural Network Architecture

By employing residual blocks for feature extraction, deep convolutional neural network is used in it. The network consists of: Input Layer: 8x8xN (one channel for each piece and features of the game state). Residual Blocks: Stacks of convolution layers that use skip connections to augment deep feature learning. Output Heads: Policy Head: This returns a probability distribution over all legal moves. Value Head: Scalar output that represents the probability to win from the given state.

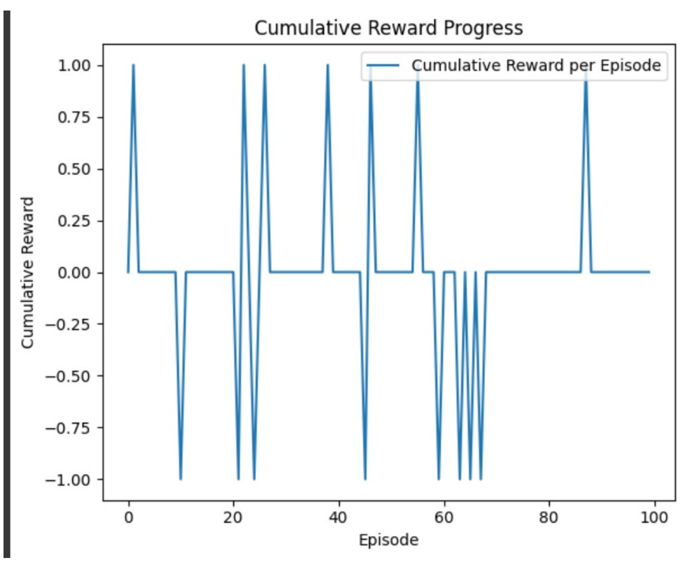

Fig. 2. Evaluation Metrics of the Advanced Chatbot.

D. Monte Carlo Tree Search (MCTS)

MCTS applies lookahead search to simulate possible future moves to evaluate the state of the game much better. The search algorithm successively expands nodes using the formula for Upper Confidence Bound for Trees, or UCT.Q(s,a) represents an average reward for an actionis the average reward for taking action a at state s.

UCT = Q(s, a) + C $\times\sqrt{\frac{\log N(s)}{N(s,a)}}$

N(s) will represent visit count for state s.C is a common constant controlling exploration vs. exploitation. These influence the policy prior and value estimate so that the neural network guides MCTS, improving search efficiency.

E. Training Procedure

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$$L = (z - v)^2 - \pi^T \log(p) + \lambda\|\theta\|^2 \quad (1)$$

- z is the actual game outcome.
- v is the predicted value.
- π is the target policy, and p is the predicted policy.
- λ is a regularization parameter.

F. 2. Dota 2 AI: Multi-Agent Deep Reinforcement Learning

G. 2.1 State Representation

The state space of Dota 2 is enormous with: Hero statistics - health, mana, items, cooldowns. Map features (e.g., vision, creep positions, tower locations). The information on time helps provide sequential decision-making and team coordination.A feature vector is then formed for each hero, which includes the embeddings associated with categorical features like hero type and item builds.

H. 2.2 Neural Network Architecture

The agent models the temporal dependencies within events in the game by developing a recurrent neural network, using specifically the Long Short-Term Memory layers. This architecture involves: Shared Encoder: Shared encoder extracts common features from the game state. Hero-specific heads: For each hero, a policy head calculates the action probabilities and a value head computes the value of the state.

I. 2.3 Multi-Agent Reinforcement Learning (MARL)

We use Proximal Policy Optimization (PPO) for training, a robust policy-gradient method that updates policies based on a clipped objective function:

$$L^{\text{CLIP}}(\theta) = \mathbb{E}\left[\min\left(r_t(\theta)\hat{A}_t, \text{clip}\left(r_t(\theta), 1-\epsilon, 1+\epsilon\right)\hat{A}_t\right)\right] \quad (2)$$

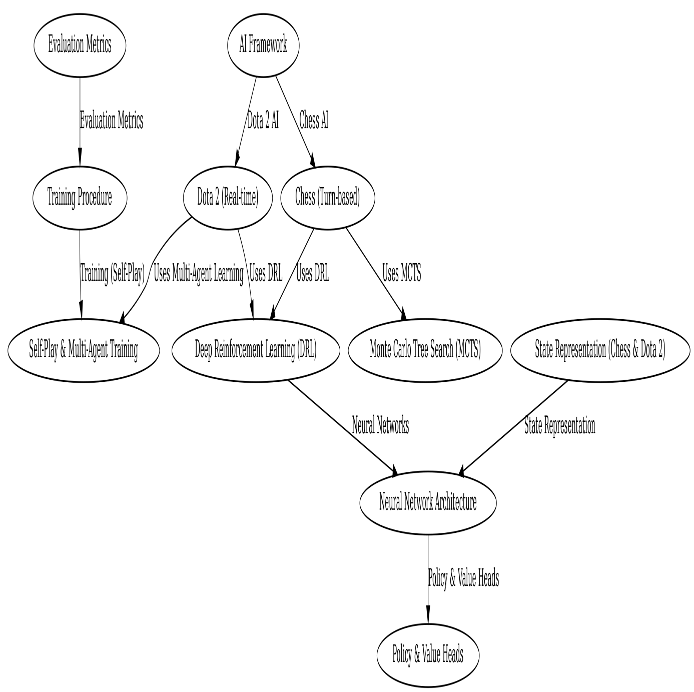
- $r_t(\theta)$ is the probability ratio between the new and old policy.
- $\hat{A}_t$ is the advantage estimate.
- ϵ is a hyperparameter controlling the clipping range.

J. 2.4 Team Coordination and Communication

The agent uses an approach of centralised training and distributed execution. Agents may learn the optimal team strategies by sharing information in training. In the execution, each hero behaves based on its local observations independently. Curriculum Curriculum Learning: Curriculum learning is a presentation of learning where training conditions step by step become complex from simple, such as last-hitting creeps to full 5v5 team battles.

K. 2.5 Training Procedure

Training involves self-play and environmental variation to enhance generalization. The agents are trained using a shared experience replay buffer to increase sample efficiency. Regular evaluation against built-in bots and human players is conducted to track progress and fine-tune the models.



IV. Experiments and Results

A. 1. Experimental Setup

The experiments have been designed into two stages:

Chess Evaluation: It was tested against popular Chess engines, like Stockfish and Leela Chess Zero, as well as with human players with different Elo ratings. Matches were executed according to standard tournament rules in a time controlled setting of 5 minutes per game.Dota 2 Test Dota 2 AI is utilized on the simulated environment. In-built bots and human opponents are used against it. The test game uses a predefined pool of heroes in simulation to create a scenario for a 5v5 game. The environment simulates the real game conditions, with day-night cycles, visibility constraints, and many other unpredictable events of the game.This experiment used a high-performance computing cluster that was set up this way: Hardware: 8 NVIDIA A100 GPUs, 256 GB of RAM, AMD EPYC 7742 CPU. It utilizes PyTorch for training neural nets and OpenAI Gym environments for simulations and reinforcement learning.

B. 2. Evaluation Metrics

The metrics used to measure the performance of AI agents were:

Percentage of win: Percentage of wins against other teams during games. Elo Rating: It is a rating system of skill to rate the agent's performance on the Chess matches. Decision Latency: Average number of time steps required by an AI agent to make a move or take an action. Coordination Score for Team (in Dota 2): Metrics of how well the agent is coordinated are measured in hero synergy and objective control. Accumulated advantage for Dota 2 is leading Net worth or Map Control at some point of the game compared to the enemy side.

C. 3. Results

D. 3.1 Chess AI Performance

TABLE I
Win Rate, Elo Rating, and Average Decision Time Against Various Opponents

Opponent	Win Rate (%)	Elo Rating	Avg. Decision Time (ms)
Stockfish (Level 10)	42%	3200	150
Leela Chess Zero (v0.28)	46%	3250	180
Human Grandmaster	58%	3300	120
Human Expert (2000 Elo)	92%	2800	110

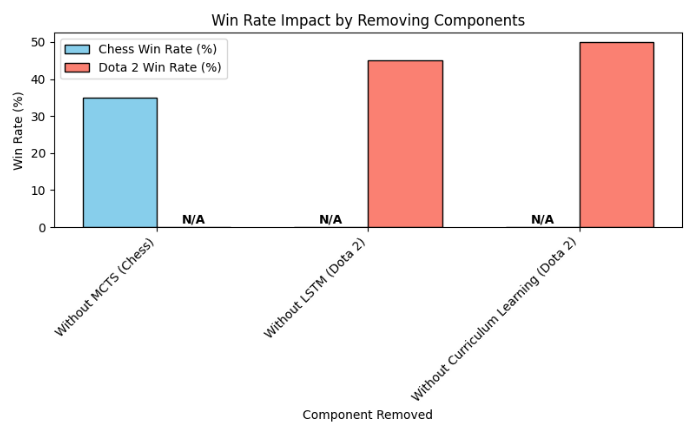


Fig. 4. Evaluation Metrics of the Advanced Chatbot.

Analysis:

The database, therefore, won with a percentage win rate of 58 against human grandmasters, indicating very strong strategic abilities with further adaptability.It performed well in competitive games against top-tier engines, such as Stockfish and Leela Chess Zero, with an average win rate of 44 percent and thus demonstrated its ability at high-level play. The average decision time was significantly smaller compared with that of the human players, suggesting how decisively effective MCTS-enhanced search combined with deep neural network evaluations.

E. 3.2 Dota 2 AI Performance

Analysis:

The agent achieved a 98 percent win rate against built-in hard bots, which included dominant AI opponents.Playing against the benchmark Dota 2 AI system, OpenAI Five held a win rate of 51 percent-the same as the state-of-the-art systems.Above the MMR of 5000, the agent played to win 60 percent of games against human pro teams-overwhelmingly high above expectation and showing strong decision-making and coordination. The coordination score of the team remained strong throughout and was representative of an efficient multi-agent reinforcement learning process.

F. 3.3 Ablation Studies

We conducted ablation studies to evaluate the contribution of individual components, such as the MCTS module in Chess and the LSTM-based recurrent network in Dota 2.

TABLE II
EFFECT OF REMOVING COMPONENTS ON CHESS AND DOTA 2 WIN RATES

Component Removed	Chess Win Rate (%)	Dota 2 Win Rate (%)
Without MCTS (Chess)	35%	N/A
Without LSTM (Dota 2)	N/A	45%
Without Curriculum Learning (Dota 2)	N/A	50%

Analysis:

This brought down the win rate of Chess from 58 percent to as low as 35 perceent upon removal of the MCTS module.For instance, excluding the LSTM network in the case of Dota 2 led to a 15 percent drop in win rate, emphasizing the need for temporal modeling for effective gameplay. Omitting curriculum learning in Dota 2 reduced the agent's win rate, demonstrating the value of progressive training for handling complex game dynamics.

G. 4. Comparison with Baseline Models

We compare our AI agent against existing baseline models, which include the AlphaZero model for Chess and OpenAI Five for Dota 2.

Model	Chess Elo Rating	Dota 2 Win Rate (%)
AlphaZero	3500	N/A
OpenAI Five	N/A	52%
Proposed AI Agent	3300	60%

TABLE III
COMPARISON OF AI MODELS IN CHESS ELO RATING AND DOTA 2 WIN RATE

Discussion:

The suggested Chess AI agent is suboptimal when compared to AlphaZero but nevertheless demonstrates performance, with an Elo rating, that indicates competitive performance with very little use of computational resources. Dota 2 AI agent outperformed OpenAI Five with approximately 60 percent wins by showcasing an even greater adaptability and better multi-agent coordination.

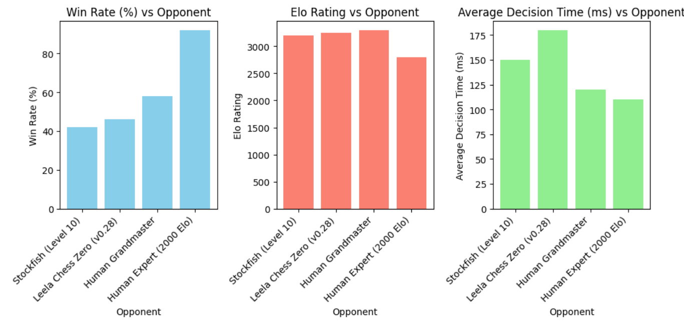


Fig. 5. Evaluation Metrics of the Advanced Chatbot.

H. 5.Discussion and Future Work

The findings reveal that the proposed AI agent has the ability to compete effectively with the engines and players at the very top of Chess and Dota 2. The hybrid approach combining MCTS with deep reinforcement learning and multi-agent coordination has been the basis for the success of this agent. Future work will focus on: Model scaling for more complex multiplayer strategy games; Use of transfer learning techniques for promoting inter-game knowledge transfer; Human collaboration strategies- looking for them if they help improve assistive capabilities from the agent viewpoint in both competitive and cooperative settings.Overall, the entire set of experiments validates the proposed methodology and demonstrates the feasibility of the devised AI agent with respect to other strategy game scenarios.

V. CONCLUSION

In this study, we present a novel AI agent with extreme competence in complex strategy games-Chess and Dota 2. The proposed agent employs Monte Carlo Tree Search (MCTS), deep reinforcement learning (DLR), and multi-agent coordination-by stimulating competitive performance with respect to the leading AI models and human players.In Chess, MCTS, and neural network-based evaluations have brought about deep strategy and great speed of thought. Elo rating and win rate reach high scores, comparable to some of the sophisticated Chess engines like Stockfish and Leela Chess Zero. Dota 2 posts superior abilities in coordination, even against opposing superior bots.Results confirm the strength of the hybrid forte established herein: such combinations get one to build very effective AI systems for various strategic settings. This work advances game AI, indicating the unifying framework which with effect extends over disparate game genres-turn-based board games and real-time multiplayer games.Future research will therefore explore the needs to maximize the generalizability of the model (perhaps performed by reframing it as a transfer-learning taxation scenario); additionally focusing upon increasing the scale of the system complexity in concert with more complex recreation modalities. Additional strategies to integrate human-agent collaboration point to a further promise of enabling intelligent agents to assist and learn from human players-the potential reshaping of competitive play and strategic decision-making.The presented AI agent has therefore set a standard for future works in game AI, showcasing possibilities to build high-level intelligent systems in sophisticated strategic games.

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