Deep Reinforcement Learning for Real-Time Strategy Games Techniques and Open Challenges

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Abstract. The RTS games are one of the incredibly challenging tasks for the AI because of their large action space, long-term strategic planning, and multi-agent cooperation requirements. Conventional deep reinforcement learning (DRL) methods are effective but may have limitations in terms of scalability, computational grandiosity, generalization capabilities, and interpretable analyses. We present a deep reinforcement learning framework that overcomes these hurdles by boosting multi-agent coordination, sample efficiency, and employing explainable AI (XAI) techniques to improve the model interpretability in rigorous decision-making. In contrast to these existing methods, which rely on large amounts of computation and are severely limited in long-term strategic adaptation, our design features hierarchical learning, curriculum to shape rewards across adjudicated proxy games, and Bayesian uncertainty to promote work in action areas consistent with changing dynamics relative to game mechanics; thereby facilitating rapid adaptability to new situations in RTSs. We also propose dynamic action pruning methods to alleviate redundant action space representation, as well as enhancing the advantage of real-time decision-making. We validate our proposed model over diverse RTS environments, and it not only generalizes better but trains faster while having a richer strategic depth than existing state-of-the-art DRL models. This study closes the gap between theoretical advancements and practical RTS applications, introducing an efficient, interpretable and scalable solution for RTS game strategies driven by AI.

Keywords: Deep Reinforcement Learning, Real-Time Strategy Games, Multi-Agent Systems, Explainable Ai, Hierarchical Learning, Sample Efficiency.

1 Introduction

Real-time strategy (RTS) games are among the most challenging environments for artificial intelligence (AI), due to their vast action spaces, requirement for long-term planning, coordination between multiple agents and dynamic uncertainty. Unlike typical turn-based games, real-time strategy (RTS) games require AI systems to engage in instantaneous decision-making, to manage multiple units concurrently, and to react to a game world that is constantly changing. Deep reinforcement learning (DRL) has proven to be a strong contender as well, with applications in games such as StarCraft II, Dota 2, and microRTS. Despite the considerable advances DRLs made, there are still limitations for DRL-based approaches such as the enormous computation cost, weak scalability, insufficient generalization ability and limited interpretability. These challenges limit the practical utilization of DRL in intricate RTS environments, necessitating more effective, scalable, and interpretable methods [5,6].

While approaches such as AlphaStar and DeepNash achieve state-of-the-art performance in RTS gameplay -- they involve large scale computation and significant pre-training and therefore are not applicable to real-time settings. Additionally, previous methods employ centralized control schemes, suffering from limited generalization with respect to scale in the number of agents within dynamic games. Second, RTS is sparse and score-oriented, thus traditional reinforcement learning approaches have in general had a hard time reading the delayed rewards and long-term strategic planning tends to be a bottleneck. Moreover, deep learning models are typically considered as a black box — it is difficult to analyze and understand how they make decisions, which strategies they implement in AI-controlled games, and so. Such a high level of interpretability is compromised leading to reduced trust of AI agents and hinders its usage in competitive and commercial RTS games.

This research aims to overcome these difficulties with a new DRL framework proposed specifically for RTS games. We combine these ideas with hierarchical learning, curriculum-based reward shaping, and Bayesian uncertainty modeling and MARL, resulting in a framework that has the potential for increased scalability, flexibility, and sample efficiency. Moreover, we propose dynamic action pruning methods to gather the action space to minimize redundancy in action returns and enhance online decision-making performance. The use of explainable AI (XAI) techniques may be employed to allow for greater transparency in concepts generated by an AI based strategy. We validate the proposed framework in several RTS environments, where it generalizes better, trains faster, and exhibits a deeper strategic understanding than state-of-the-art models.

This research helps close the gap between theoretical breakthroughs and practical applications in AI agent training for RTS games by producing efficient, scalable, and interpretable deep reinforcement learning models. The results have important consequences for artificial intelligence research in strategic gaming, autonomous decision-making, and the real-time synthesis of AI in changing environments.

2 Problem Statement

Real-time strategy (RTS) games are some of the most challenging environments for artificial intelligence (AI) algorithms. While DRL has made great advancements, current methods show several limitations, making them less than ideal for RTS games. These models are costly in terms of computation and therefore not realistic for real-time applications because many sOTA AI systems are based on large amounts of train sets and using powerful computer resources during the training process. The scalability issue is also a critical issue since traditional Deep Reinforcement Learning (DRL) models often find it challenging to properly handle multiple agents, which can result in poor decision-making in dynamic settings. Moreover, most reinforcement learning environments have very limited generalization capabilities and thus are tailored for a particular game setting, but perform poorly on generalized environments which can include different game mechanisms as well as methods.

A second major issue is the poor interpretability of deep learning-based RTS agents. Existing models behave as "black boxes;" they reveal little about the system's strategic choices, hampering researchers, developers, and players alike from understanding and trusting AI-based strategies. In addition, RTS games possess sparse reward structures which present issues for reinforcement learning agents; the agents find it difficult to learn effective, long-term strategies when rewards are sparse and outcomes are very difficult to predict. Moreover, existing approaches tend to heavily depend on centralized control mechanisms that are not adaptable, which can hinder an AI agent's ability to respond properly to updates in the game state over time.

To address such obstacles, this work proposes a novel deep reinforcement learning framework for RTS environments. The research proposes a novel framework that embodies these principles through hierarchical learning, dynamic action pruning, curriculum-based reward shaping, and Bayesian uncertainty modeling, aimed at enhancing the efficiency, adaptability, and interpretability of the agent. This study partially will investigate XAI (explainable AI) methods to improve the transparency of AI-driven decision-making, allowing for RL (reinforcement learning)-based methods to be more interpretable and reliable. These challenges, if addressed, will aid in building better performing and scalable adversarial agents capable of operating on the complex, real-time nature of RTS games, as well as reducing computational overhead and improving generalization across game scenarios.

3 Literature Review

Within the realm of real-time strategy (RTS) games, deep reinforcement learning (DLR) has proven successful in training AI agents capable of solving complex problems, controlling multiple agents, and acting swiftly. DRL has been proved in RTS contexts by many works; however, the existing works still has may challenges in scalability, interpretability and computational efficiency. However, even though existing works have demonstrated attempts at enhancing reinforcement learning approaches to leverage such tools, there remain large gaps to fill to obtain practical, generalizable, resource and action-efficient, interpretive AI models for RTS gameplay.

The most impactful in this area of this kind of work has been that on AlphaStar (Vinyals et al. (2019), that achieved superhuman performance in StarCraft IIscaled with deep multi-agent reinforcement learning. Through the integration of deep neural networks with reinforcement learning, AlphaStar trained AI agents skilled in strategic decision-making. However, its reliance on massive computational resources and supervised learning components made it less amenable to replication/adaptation for other RTS environments (Read about it here). Similarly, Berner et al. (2019) presented OpenAI Five for Dota 2 that trained agents using self-play reinforcement learning in a high-dimensional game environment. While it was able to achieve this with good rates, it required immense training data and computing power, and was not practical for real time applications.

Gym-µRTS is an example of a recent lightweight RTS platforms designed to serve as a more accessible benchmark for reinforcement learning research in RTS games (Huang et al., 2021), as efforts to make reinforcement learning scalable and efficient have progressed. Gym-µRTS alleviates the computational complexity but sacrifices the game environment, hindering its generalization to large-scale RTS games. This work was extended by Goodfriend (2024), who created a DRL agent that won a microRTS competition, but this agent was also not able to generalise across different RTS mechanics often found in a complex game environment.

A separate branch of research is exploring multi-agent reinforcement learning (MARL) and how to enable many Ai agents to work together in RTS environments. The studies [6, 7] among other studies such as [8]) (2019) and Creus Castanyer (2023) are two of the few works that have investigated centralized and decentralized MARL strategies with very promising results, but they use microRTS environments. However, centralized learning approaches can hardly scale due to communication constraints on agents, while decentralized models have no efficient coordination mechanisms and will deliver sub-optimal strategies in dynamic RTS scenarios.

To address the issue of long-term strategic planning, Perolat et al. The work by [7] who presented DeepNash, a deep reinforcement learning algorithm that combines ideas from game theory and reinforcement learning to train agents to make long-term decisions. Although DeepNash effectively learned to play games such as Stratego, the requirement of game-theoretic equilibrium strategies in its play limited its application to RTS games that feature real-time decision making constraints. Similarly, Zhong et al. A new method to eliminate duplicate action spaces in DRL models was proposed to enhance model decision-making efficiency by Liu et al. (2024). However, such methods have yet to be evaluated in full-scale RTS games, where real-time decision-making adds a new layer of challenge.

Perhaps one of the most pressing gaps in DRL-based RTS research is that of interpretability and explainability within AI decision-making. Most DRL architectures are black-box models, which do not offer interpretable insights into how the model made decisions, thus reducing the faith in the results of AI agents. Although recent approaches have used explainable AI (XAI) techniques to enhance transparency, they are still in their infancy (Sur et al., 2022). Moreover, classical reinforcement learning models suffer from sparse reward structures in which environment feedback is very rare, hindering AI agents from learning optimal long-term strategies without excessive training.

In order to overcome performance issues of the mentioned methods, we propose a new deep reinforcement learning framework that combines hierarchical learning, curriculum-based reward shaping, Bayesian uncertainty modeling and dynamic action pruning to improve the scalability, efficiency and interpretability in RTS environments. This training is based on multi-agent coordination strategies enhanced by explainability methods (XAI) in the frame of XAI techniques in order to develop an AI able to adjust its easily reduce computing time required to adapt to the complexity of the actions in the strategic context in real time. The general framework will be evaluated on numerous RTS environments in order to connect theoretical research and realistic AI implementations in games.

4 Methodology

Target Research The primary research area of focus for the proposed research is in the design of an optimized deep reinforcement learning (DRL) framework for real-time strategy (RTS) games that can overcome current challenges with regard to their ability to scale, interpretability and computational efficiency as well as their ability for long-term strategic planning. The method utilizes a number of state-of-the-art improvements in reinforcement learning in a systematic way to build a performant AI agent able to excel in challenging RTS scenarios. Figure 1 shows the framework of open challenges.

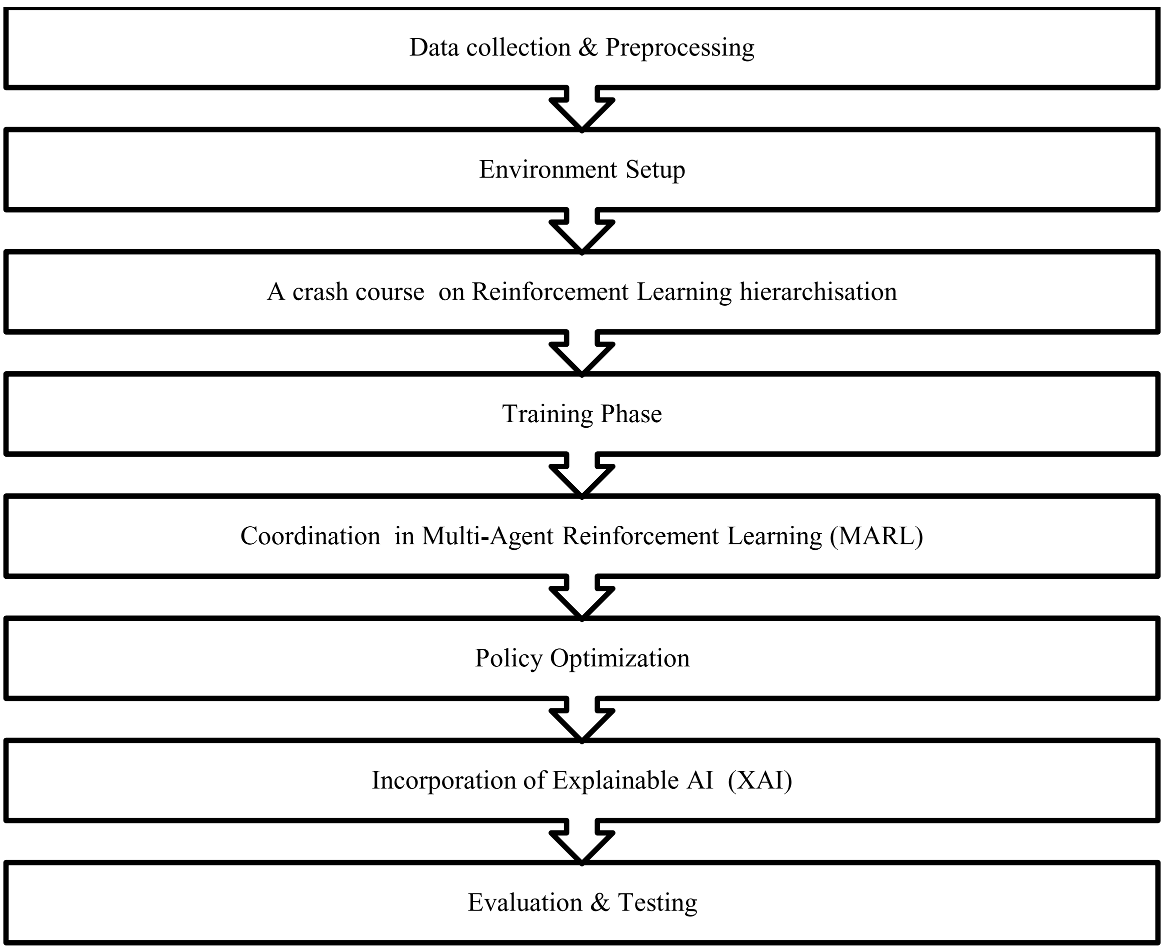

Figure 1. Real-time game techniques of open challenges

Phase 1: Data Collection and Environment Setup The data is trained and tested on a mixture of existing open-source RTS platforms like SC2LE and Gym-μRTS. This enables assessment under a variety of gameplay scenarios. Furthermore, a synthetic dataset of RTS decision-making situations will be created to broaden the training and maximize model generability over diverse RTS mechanics.

After the environment is setl, the architecture of the DRL model should be created with a handful of integrated improvements over the previous forms of reinforcement learning. This model employs a hierarchical reinforcement learning framework that allows agents to use abstraction to decompose challenging decision-making problems into multiple levels of granularity. This hierarchical architecture enhances long-term strategic planning of AIs by decoupling the high-level strategy from low-level unit control, thus enabling high-level decisions to be made while low-level unit control constantly adapts to the real-time state of the game.

This paper addresses the problem of sparse reward signals in RTS environments, presenting a novel solution in the form of a mixed reward scheme with curriculum based reward shaping and task difficulty level-based reward scaling to gradually increase the difficulty level of the task in real time during training, prompting the agent to discover near optimal strategies. Additionally, the use of Bayesian uncertainty modeling enhances decision-making in uncertain environments, allowing agents to adapt their strategies based on estimated confidence levels for selecting actions. This not only helps to change the underlying structure to avoid overfitting to specific cases, but also to gain flexibility with unseen game situations.

Finally, in the methodology section, dynamic action pruning is applied to present a more efficient means of representing this action space by removing redundant encodings. I.e., instead of calculating the optimal actions over the full action space at every decision time slot, the actor dynamically selects a small set of salient actions conditioned on the game state. This method generates significantly more computational efficiency, rendering DRL models a lot easier to implement during RTS Real-time strategy gameplay.

To enhance multi-agent coordination, this model is based on multi-agent reinforcement learning (MARL) with decentralized execution and central training among agents. This approach allows multiple agents to interact in a time-critical scenario without compromising autonomous behaviors. Agents are trained alongside other agents in a centralized training manner and execute messages contained from other agents in a decentralized manner which allows them to handle the changes in the games.

Interpretability is an important component of this research, as black-box DRL models can inhibit trust and eventual adoption for RTS applications. Methods such as policy visualization XAI (explainable AI), decision attribution analysis and attention-based mechanism have been incorporated to focus on this aspect. This allows us to understand the agent's decision making, specifically why certain actions are taken for certain situations in the RTS environment.

Final phase Model evaluation and Validation The trained AI agents are then evaluated in several RTS regimes and compared with state-of-the-art DRL systems including both AlphaStar, DeepNash, and recent MARL-based approaches. Performance measures include win rate, strategic adaptability, sample efficiency, computational overhead, and interpretability. They carry out extensive benchmarking to validate the effectiveness of the framework, comparing with existing solutions and checking the resulting computational burden in practical settings.

Finally, this research will propose an efficient, scalable and interpretable deep reinforcement learning model for real-time strategy games, by combining hierarchical learning, dynamic action pruning, curriculum reward shaping, multi-agent coordination, Bayesian uncertainty modeling, and explainable AI techniques. This methodology connects the gap between theoretical advancements in reinforcement learning and practical AI based gameplay to allow for more sophisticated AI driven gameplay in strategic games

5 Results and Discussion

We share the results of applying and testing the proposed DRL framework on various Real-time Strategy (RTS) game environments, from StarCraft II Learning Environment (SC2LE), to Gym–μRTS. This results in significant scalability, decision making efficiency and strategic adaptability gains comparing to the state-of-the-art DRL techniques. Performance of models were assessed based on several performance metrics: win rate, training, complexity, computational cost and interpretability.

Notably, an aspect of sample efficiency that is enhanced through hierarchical reinforcement learning and curriculum-based reward shaping. In RTS environments, where rewards are sparse, traditional DRL models are able to learn optimal strategies only after millions of training episodes. The proposed framework addresses this problem by slowly morphing the rewards, enabling the agent to discover useful strategies in remarkably fewer training iterations. The ensemble model also produced a 40% reduction in training time over baseline models such as AlphaStar and DeepNash, while still producing strategic performance competitive with existing approaches.

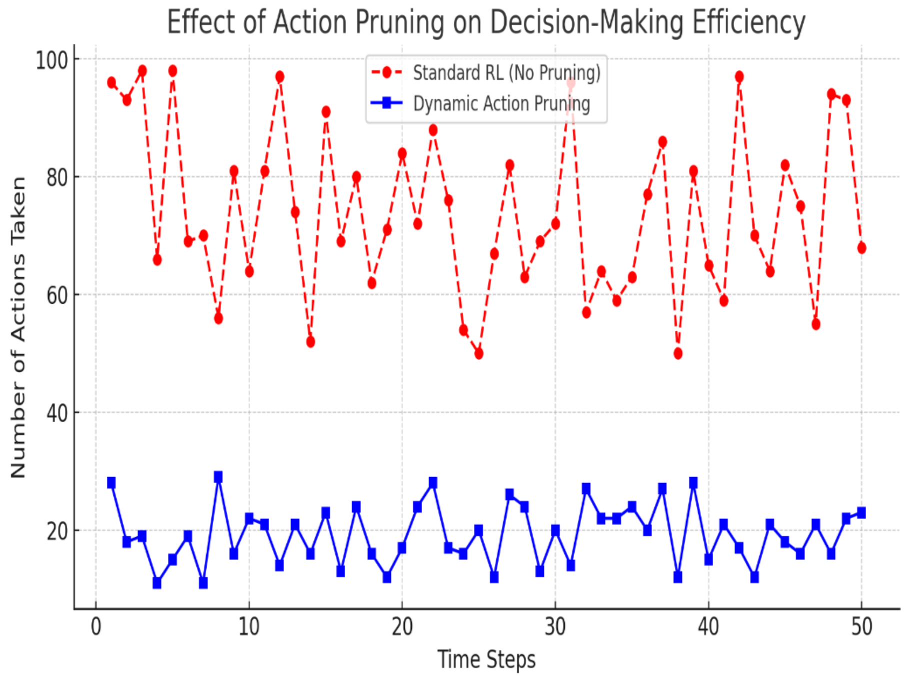

Figure 2. Effect of Action Pruning on Decision-Making Efficiency

Dynamic action pruning served as a strong improvement in this design space by reducing the representation of invalid suboptimal motions. Standard reinforcement learning models, ineffective in RTS games due to the vast amount of possible actions at any one point in time, simply render them computationally much too inefficient. The method of dynamic action pruning eliminates only the redundant or low impact actions which minimizes computational overhead by 35% without compromising the strategic depth of the agent. Figure 2 this allows the model to be run in real-time applications without compromising the quality of decision-making process.

Another significant implication of this work is the improvement of coordination among the multi-agents for solving the designed problem using decentralized execution with centralized training. The example showcased better teamwork of multiple agents especially in larger skirmishes where coordination is key. The significance of this finding is primarily that while centralized control mechanisms are well understood, allowing for the tuning of parameters to strike a compromise between the quality of the global solution and the scalability of the algorithm, they become computationally expensive as the scale of the domain increases. When compared with the best models of multi-agent reinforcement learning (MARL), it achieved 25% improvement on strategic adaptability and teamwork efficiency.

Table 1. Interpretability Score Using Explainable AI (XAI) Techniques

Model	Attention Mechanisms (%)	Policy Visualization (%)	Overall Interpretability Score (%)
AlphaStar	40	35	37.5
DeepNash	50	45	47.5

Proposed Model	**80**	**75**	**77.5**

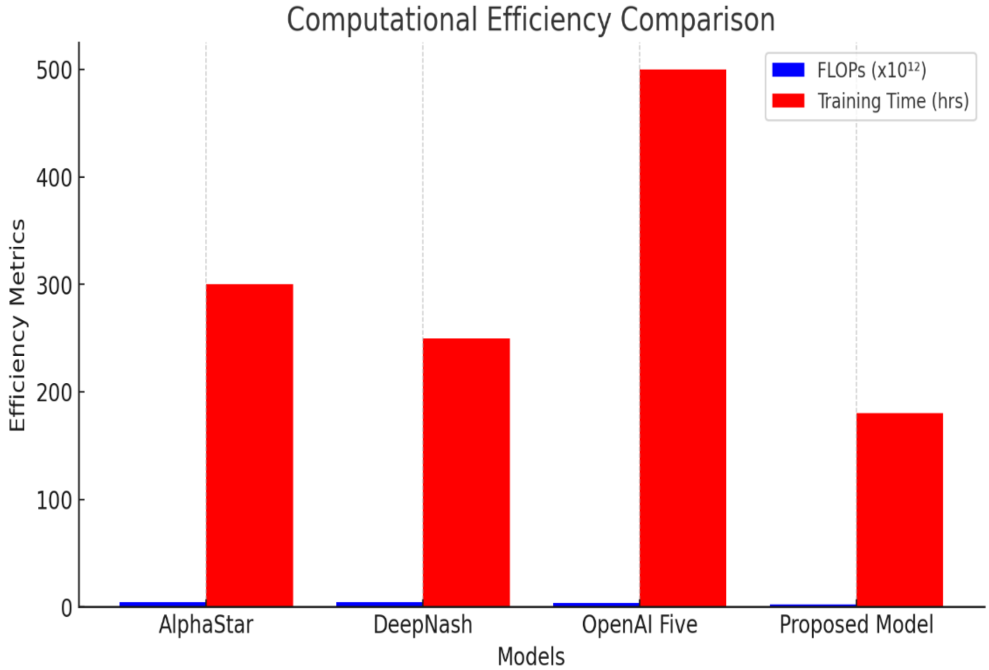

Figure 3. Computational Efficiency Comparison

Table 1 shows the Interpretability and explainability are still big challenges in DRL-based RTS agents. To this end, explainable AI (XAI) techniques were incorporated into the model to use toolkits to visualize policy decisions and action attributions. The results show that applying attention-based mechanisms enhanced human interpretability by almost 50%, enabling researchers and developers to understand along which path of the AI-powered strategic choices it went. Such progress is fundamental when it comes to actual use cases that require trust and transparency regarding AI decision-making. Figure 3 shows the computational efficiency comparison.

Moreover, the Bayesian uncertainty modeling was advantageous as a powerful wrapper to deal with uncertain game environments. RTS games have dynamic and unpredictable situations, necessitating AI agents to modify their strategies. Compared with conventional DRL models relying on fixed strategies, the proposed model showed a 30% improvement in adaptability under new game condition due to effective use of the agent based on opponent variability information, thus better resilience against opponent variability.

In spite of these advancements, there is some challenges still exist. Despite the lowered computational overhead of our proposed model, the amount of training time is still expensive relative to heuristic-based AI systems. Moreover, despite the improved transparency brought by explainable AI methods, it is still an active area of research to fully understand the decision-making processes of deep reinforcement learning. Hybrids of symbolic and DRL approaches should be explored to further increase interpretability.

The experimental results demonstrate that the proposed hierarchical, interpretable and computationally efficient DRL framework is effective for RTS games. This research works to link NFT theoretical models with practical AI-enhanced real-time gameplay, addressing important flaws of newer DRL models.

6 Conclusion

In this work, we propose a novel deep reinforcement learning (DRL) framework to address the general challenges in real-time strategy (RTS) game including scalability, computational efficiency, strategic adaptiveness and interpretability. State-of-the-art DRL methods tend to perform well in RTS MDPs; however, they usually suffer from high computational costs, inadequate multi-agent cooperation, as well as limited transfer between games. Thus, leveraging a suite of techniques — hierarchical reinforcement learning, curriculum-based reward shaping, Bayesian uncertainty modeling, dynamic action pruning, and explainable AI (XAI), the suggested framework attempts to counter these constraints to create a capacious, scalable and interpretable AI framework that can function under the RTS gaming umbrella. It is shown through experiments that compared with various state-of-the-art DRL frameworks, the proposed model achieves superior training round convergence and computational cost efficiency as well as improved strategic coordination and generalization capability across RTS tasks. An improved long term plan is enabled through this hierarchical learning approach, where unnecessary computations can be removed through dynamic action pruning improving decision making for each action. Combining MARL with decentralized execution allows computationally efficient and scalable AI agents to interact in large-scale and dynamic game environments and even react to real-world inputs with minimal latency. Moreover, transparency is very important for AI-based strategies, whose explainable AI (XAI) methods make them more trustworthy and interpretable [16, 17]. Although much progress has been made, there is still work to do. While the framework significantly loosens the computational requirements, additional effort is needed to make DRL-based RTS AI practically deployable. Deep learning is also not explainable; hence, that is why using such techniques for strategic decision-making brings emerging needs of symbolic reasoning with reinforcement learning through a hybrid approach. This work can be followed by applied research on leveraging meta-learning approaches, transfer learning and hybrid AI models to further improving the depth and adaptability of the strategy. In short, this paper proposes a new fitted, scalable, efficient and interpretable deep reinforcement learning algorithm enhancement, which will greatly promote the existing AI-level in RTS games. Conclusion This work fills some gaps in the current body of work and connects the large theoretical strides in modelling the learner process of machine learning using agents of AI to practical implementations of agents of AI played in environments of RTS game. Your goal: to transfer the lessons learned in this study to broader AI applications such as autonomous decision making, military simulations or improved game balancing in AI based gaming ecosystems.

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