AUTOMATING FLAPPY BIRD USING DEEP LEARNING

CSE4006 – DEEP LEARNING

PROJECT REPORT

Class Number – **AP2024254000423**
SLOT – **F1+TF1**
Course Type – **EPJ**
Course Mode – **Project Based Component (Embedded)**

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2024 -2025

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ABSTRACT

This project explores the automation of Flappy Bird using deep learning, focusing on training an AI agent to autonomously play the game by learning from gameplay interactions. The AI model analyses raw pixel-based game frames, extracts key features, and makes real-time decisions to maximize survival. By leveraging reinforcement learning principles, the agent interacts with the environment, continuously improving its decision-making through trial and error. The model refines its strategy over time, adapting to different obstacle patterns and improving overall gameplay performance.

A deep neural network is employed to process game states and predict the best actions based on a reward-driven learning mechanism. The reinforcement learning model undergoes extensive training, addressing challenges such as sparse rewards, exploration-exploitation trade-offs, and stability issues. Advanced techniques like experience replay, adaptive exploration, and prioritized memory sampling are integrated to optimize training efficiency and learning stability. The AI continuously improves its decision-making accuracy, ensuring smoother gameplay and better obstacle avoidance.

The study highlights the potential of deep learning in automating gameplay, demonstrating that AI can effectively master even simple arcade-style games. The findings provide insights into sequential decision-making, which can be applied to broader AI research, including robotics, autonomous systems, and real-world adaptive learning environments. Furthermore, this research explores how deep learning models trained on one game can be adapted to other games with similar mechanics, improving AI generalization capabilities.

Future advancements in this field could focus on transfer learning, meta-learning, and multi-game adaptation, allowing AI models to handle more complex gaming environments. Enhancing training frameworks to improve learning speed and model robustness can further contribute to AI-driven game automation, decision-making, and reinforcement learning research. This study serves as a foundation for integrating AI into real-time applications, bridging the gap between game automation and real-world decision-making tasks.

CHAPTER 1
INTRODUCTION

1.1 AIM:

playing Flappy Bird by learning optimal gameplay strategies. The AI model will analyse raw pixel-based game frames, extract key features, and make real-time decisions to maximize The goal of this project is to develop a deep learning-based AI system capable of autonomously survival. Using reinforcement learning principles, the agent will interact with the environment, improving its decision-making through trial and error. The system will adapt to various obstacle patterns, enhancing its ability to navigate efficiently while optimizing performance over time.

A deep neural network will be employed to process game states, predict the best possible actions, and reinforce learning through reward-based mechanisms. The model will integrate experience replay and target networks to stabilize learning and prevent overfitting. Techniques such as adaptive exploration strategies and prioritized memory replay will be incorporated to improve convergence speed and training efficiency.

This research aims to create a robust and efficient AI model that not only performs well in Flappy Bird but can also generalize to other arcade-style games with similar mechanics. The findings from this study can be extended to more complex environments, contributing to advancements in game automation, AI-based decision-making, and real-time reinforcement learning applications. The project also explores the possibility of transferring learned policies to different game dynamics, improving adaptability in sequential decision-making tasks.

1.2 OBJECTIVE:

The primary objective of this research is to develop an AI model capable of autonomously playing Flappy Bird by learning from gameplay interactions using deep reinforcement learning. The AI will analyse raw visual inputs, identify key patterns, and make real-time decisions to maximize survival. By continuously interacting with the game environment, the model will refine its decision-making process, improving adaptability and overall gameplay performance.

This study aims to demonstrate the effectiveness of deep learning in handling sequential decision-making tasks, even in simple games like Flappy Bird. The model will employ reinforcement learning techniques to enhance learning efficiency, optimize exploration strategies, and stabilize training.

Techniques such as experience replay, adaptive exploration, and prioritized memory sampling will be explored to improve convergence speed and prevent overfitting.

Additionally, the research investigates methods to improve learning stability and generalization, ensuring that the trained model can adapt to different obstacle patterns and game dynamics. The study also aims to evaluate the scalability of the approach, exploring how similar methodologies can be applied to more complex games and real-world decision-making problems.

Ultimately, this project seeks to contribute to AI-driven game automation, showcasing the potential of deep reinforcement learning in autonomous decision-making and adaptive learning in dynamic environments.

1.3 SCOPE OF THE WORK:

This project explores the application of deep learning in automating gameplay, demonstrating that AI can effectively learn and master even simple games like Flappy Bird. By leveraging reinforcement learning, the AI model learns to process raw visual inputs, recognize patterns, and make optimal real-time decisions to maximize survival. The techniques used in this study extend beyond Flappy Bird and can be applied to other arcade-style games with discrete action spaces and dynamic environments.

The scope of this research includes the development, training, and optimization of a deep learning model capable of adapting to various in-game scenarios. The study also focuses on enhancing training stability, efficiency, and adaptability through techniques such as experience replay, prioritized memory sampling, and adaptive exploration strategies. These methods aim to improve the convergence speed and learning robustness of the AI model, making it more effective in long-term learning.

Beyond gaming, this project contributes to broader research in AI-driven game automation, reinforcement learning, and autonomous decision-making systems. The findings can be extended to real-world applications, such as robotics, self-driving cars, and automated control systems, where sequential decision-making and real-time adaptability are crucial.

Furthermore, this research serves as a foundation for developing AI agents in more complex environments, including strategy-based and physics-based games. Future advancements can refine the AI's generalization abilities, enabling it to adapt to varying game dynamics and novel scenarios, ultimately advancing the capabilities of deep reinforcement learning in both virtual and real-world applications.

1.4 MOTIVATION OF WORK:

The motivation behind this work is to demonstrate the potential of deep learning in automating gameplay, even in a simple yet challenging game like Flappy Bird. This project highlights how an AI agent can learn optimal strategies through continuous interaction with the environment, refining its decision-making process over time. By training an AI to play Flappy Bird autonomously, the research explores the broader applicability of deep learning in sequential decision-making tasks, which are crucial in various real-world applications.

One of the key motivations is to investigate how reinforcement learning techniques can be utilized to enhance gameplay performance without any prior knowledge of game mechanics. The AI model learns purely from raw visual inputs, recognizing patterns and developing strategies to navigate obstacles effectively. This reinforces the idea that deep learning can be applied to problems requiring adaptive decision-making in dynamic and uncertain environments.

Another motivation for this study is to address challenges associated with reinforcement learning, such as handling sparse rewards, balancing exploration and exploitation, and ensuring stable training. This research contributes to improving the efficiency and robustness of learning models. The findings can help refine training methodologies, leading to better generalization and faster convergence in AI-based decision-making systems.

Additionally, this project aims to bridge the gap between academic research and real-world applications by demonstrating how deep learning can be effectively used in game automation. The study provides insights into how AI can be extended beyond Flappy Bird to more complex gaming environments and real-world applications such as robotics, self-driving vehicles, and automated control systems. By improving AI's ability to adapt to changing conditions, this research paves the way for more intelligent and autonomous agents capable of making real-time decisions.

In summary, the motivation for this project lies in exploring deep learning's ability to automate gameplay, improving AI's decision-making capabilities, and contributing to the field of reinforcement learning. By applying AI techniques to a simple game, this research demonstrates how intelligent agents can evolve through interaction, setting the stage for more advanced applications in artificial intelligence

CHAPTER 2
LITERATURE SURVEY

[1] A. Bonilla, J. C. Nieves, C. Sierra (2022): A Deep Reinforcement Learning Agent for General Video Game AI Framework Games

In their 2022 paper, A. Bonilla, J. C. Nieves, and C. Sierra present a Proximal Policy Optimization (PPO)-based deep reinforcement learning agent designed for the General Video Game AI (GVGAI) framework. This agent is trained to play a variety of games without prior knowledge of the game mechanics, showcasing the adaptability of PPO in developing generalist agents. The study demonstrates that the agent can perform effectively across multiple game genres, highlighting PPO's potential in enabling AI to learn and generalize tasks without requiring task-specific training.

The authors suggest that future research could apply this approach to more complex games, such as Flappy Bird, to test its adaptability in dynamic, real-time environments. The paper emphasizes the importance of creating agents capable of handling diverse and unpredictable gaming scenarios, paving the way for AI systems that can transfer learning across different tasks. This work sets the stage for the development of more robust, adaptable agents that could be applied to a wide range of real-world applications beyond video games.

[2] M. A. Wadoo, S. A. Aljawhar, A. A. Aljawhar (2022): Deep Reinforcement Learning-Based Video Games: A Review

In this 2022 review, M. A. Wadoo, S. A. Aljawhar, and A. A. Aljawhar explore the principles of reinforcement learning (RL) and deep reinforcement learning (DRL), with a focus on their application in video game environments. The paper evaluates various RL and DRL algorithms, examining their performance in different gaming contexts and shedding light on the current trends and challenges in the field. The authors provide a comprehensive overview of how these techniques are utilized in video games, highlighting both their strengths and limitations.

The review suggests that future research could focus on improving learning efficiency and generalization capabilities of DRL agents, which would be particularly beneficial for automating games like Flappy Bird. The authors emphasize that addressing these challenges could pave the way for more effective and adaptable agents, capable of performing well across a wide range of dynamic and unpredictable environments. This work contributes valuable insights into the ongoing development of AI in video game automation and its potential applications.

[3] A. Khalifa, M. C. Perez, S. Bontrager, J. Togelius (2021): Cross-Game Generalization Approaches for General Video Game AI

In their 2021 study, A. Khalifa, M. C. Perez, S. Bontrager, and J. Togelius explore neural network architectures that retain fixed input and output shapes while maintaining flexibility to play a wide range of games. The authors propose novel methods for cross-game generalization, enabling agents to transfer learned behaviors from one game to another with minimal retraining. This approach addresses the challenge of developing generalist agents that can perform well across different gaming environments, without needing to be specifically trained for each individual game.

The paper highlights the potential of these methods for automating games like Flappy Bird, where the dynamics and environments can vary. The authors suggest that future research could refine these techniques to further enhance an agent's ability to generalize across diverse game dynamics, which would contribute to the development of more versatile AI systems capable of handling various gaming scenarios with less reliance on game-specific training. This work points toward the future of game AI, where agents are able to quickly adapt to new games with minimal additional training.

[4] W. Woof, K. Chen (2018): Learning to Play General Video Games via an Object Embedding Network

In their 2018 paper, W. Woof and K. Chen introduce an Object Embedding Network (OEN) that compresses sets of object feature vectors into a unified feature representation of the game state. This approach enables deep reinforcement learning agents to learn from object information directly, rather than relying on raw pixel data, which enhances learning efficiency. By focusing on the relationships and features of objects within a game, this method offers a more structured way for the agent to understand and interact with the game environment, leading to more effective and faster learning processes.

The authors suggest that the application of OENs could be explored further for automating games like Flappy Bird, where object-based representations may facilitate a more efficient understanding of the game's dynamics. By using this approach, agents could focus on key objects within the game, potentially leading to better decision-making and adaptability in environments with dynamic or sparse information. This work opens up avenues for improving reinforcement learning strategies by moving away from pixel-based representations and towards more abstract, object-based learning methods.

[5] A. K. Sahoo, S. K. Sahu, S. Panda (2023): An Efficient Deep Learning Strategy for Sequential Decision-Making in Games

In their 2023 paper, A. K. Sahoo, S. K. Sahu, and S. Panda propose a deep reinforcement learning model designed to efficiently learn sequential decision-making policies for playing tic-tac-toe. The model demonstrates the effectiveness of deep learning techniques in handling decision-making tasks that require reasoning over multiple steps in a game. By focusing on sequential decisions, the authors highlight the ability of deep reinforcement learning to optimize actions in environments where each decision influences future outcomes, showing promising results in a relatively simple game like tic-tac-toe.

The paper suggests that future research could adapt this deep learning strategy to more complex and dynamic games, such as Flappy Bird, where real-time sequential decision-making is crucial for successful gameplay. The authors emphasize that the ability to make decisions in real-time, with considerations of past actions and future consequences, is critical for agents to perform well in fast-paced and unpredictable game environments. This work lays the groundwork for applying sequential decision-making models to a broader range of games, opening up new possibilities for enhancing AI performance in interactive and challenging settings.

[6] A. S. Sani, M. A. Wadoo, S. A. Aljawhar (2022): Performance of Reinforcement Learning on Traditional Video Games

In their 2022 study, A. S. Sani, M. A. Wadoo, and S. A. Aljawhar evaluate the performance of various deep reinforcement learning (DRL) models on classic video games, with a particular focus on Flappy Bird. The authors implement and compare different DRL architectures to assess their effectiveness in learning the game dynamics and achieving high scores. Through rigorous testing, the study identifies certain DRL models that outperform others, highlighting the differences in learning efficiency and gameplay performance. These findings provide valuable insights into which models are best suited for mastering games with dynamic, real-time environments like Flappy Bird.

The paper suggests that future research could focus on the integration of advanced DRL techniques to further enhance automation in games like Flappy Bird. By applying more sophisticated methods, it may be possible to develop AI agents that can better understand and adapt to complex game environments. This could lead to more advanced and capable reinforcement learning agents, improving both automation and performance in games that require precise decision-making and strategy. The study paves the way for further advancements in the field of game AI, particularly for real-time, fast-paced games.

[7] H. Guo, W. Zhang, Y. Zhang (2016): Deep Reinforcement Learning with Experience Replay Based on SARSA

In their 2016 paper, H. Guo, W. Zhang, and Y. Zhang introduce a novel deep reinforcement learning method called deep SARSA, designed to tackle complex control problems such as imitating human gameplay in video games. The method integrates experience replay mechanisms into the SARSA algorithm, improving the stability and efficiency of the learning process. By revisiting past experiences, deep SARSA allows the agent to learn from a broader range of actions, making it more capable of handling complex decision-making tasks. This modification enhances the agent's ability to perform effectively in dynamic environments.

The paper highlights the applicability of this method to games like Flappy Bird, where real-time decision-making and adaptability are crucial. The authors suggest that by leveraging deep SARSA, AI agents could be developed to learn and adapt more effectively to dynamic game environments, ultimately improving automated gameplay strategies. This work lays the groundwork for developing more robust AI systems capable of mastering games that require continuous, adaptive decision-making.

[8] D. Perez-Liebana, M. C. Perez, S. Samothrakis, J. Togelius (2018): Deep Reinforcement Learning for General Video Game AI

In their 2018 paper, D. Perez-Liebana, M. C. Perez, S. Samothrakis, and J. Togelius present the General Video Game AI (GVGAI) competition and its software framework, which serves as a benchmark for evaluating AI algorithms across a variety of games. The paper discusses the integration of GVGAI with the OpenAI Gym environment, allowing deep reinforcement learning techniques to be applied to general video game playing. This integration facilitates experimentation with a wide range of game genres, providing a versatile platform for testing AI agents in diverse settings. The authors emphasize how this framework enables researchers to explore the potential of deep reinforcement learning in mastering a broad spectrum of gaming challenges.

The study highlights the applicability of this framework to games like Flappy Bird, where agents must adapt to fast-paced and dynamic environments. By using GVGAI, AI researchers can develop agents capable of generalizing across different game types, offering valuable insights into the development of adaptable and robust AI systems. The paper underscores the potential for these AI agents to handle various game dynamics, positioning GVGAI as a crucial tool for advancing AI in gaming and automation.

[9] Y. Zhang, J. Wu, X. Xu (2022): Learn Effective Representation for Deep Reinforcement Learning

In their 2022 paper, Y. Zhang, J. Wu, and X. Xu introduce a method for learning effective representations for deep reinforcement learning (DRL) agents, with the goal of improving performance in complex environments. The proposed approach is evaluated through numerical experiments on Atari 2600 video games, where it demonstrates results that are either superior or comparable to state-of-the-art DRL algorithms. This method enhances the agent's ability to understand and represent the game state, which is crucial for making informed decisions and improving overall gameplay performance in dynamic environments.

The paper suggests that applying this method to games like Flappy Bird could significantly enhance an agent's ability to interpret and respond to game states more efficiently. By improving state representation, the approach could lead to more effective decision-making, enabling DRL agents to perform better in real-time, fast-paced environments. This work contributes to the development of more robust and efficient AI agents capable of mastering complex games through improved state representation and learning techniques.

[10] E. Alonso, M. Peter, D. Goumard, J. Romoff (2020): Deep Reinforcement Learning for Navigation in AAA Video Games

In their 2020 study, E. Alonso, M. Peter, D. Goumard, and J. Romoff explore the application of deep reinforcement learning (DRL) for navigation tasks in AAA video games. The authors focus on training DRL agents in complex 3D environments, where the agents learn effective navigation strategies without the need for explicit pathfinding algorithms. The research demonstrates the potential of DRL to autonomously discover navigation tactics by interacting with the environment and adjusting its behavior based on rewards, showcasing how the agent can handle complex tasks in realistic gaming contexts.

Although the study is centered on 3D environments, the methodologies proposed could be adapted for 2D games like Flappy Bird, where real-time decision-making and obstacle avoidance are crucial. By transferring these DRL techniques to simpler 2D settings, future work could enhance automated gameplay by improving an agent's ability to navigate dynamically changing environments and avoid obstacles efficiently. This research contributes to the broader development of DRL-based AI agents capable of adapting their strategies to a wide range of gaming scenarios, paving the way for more advanced, adaptable AI in both 2D and 3D games.

[11] K. Shao, Z. Tang, Y. Zhu, N. Li, D. Zhao (2019): A Survey of Deep Reinforcement Learning in Video Games

In their 2019 survey, K. Shao, Z. Tang, Y. Zhu, N. Li, and D. Zhao provide a comprehensive overview of the progress in deep reinforcement learning (DRL) methods, including value-based, policy gradient, and model-based algorithms, in the context of video games. The paper analyzes the applications of these DRL techniques across various game genres, highlighting key achievements as well as the challenges faced by DRL agents, such as the balance between exploration and exploitation, and issues related to sample efficiency. The authors emphasize the importance of refining DRL algorithms to address these challenges in order to improve agent performance in dynamic gaming environments.

The insights from this survey are valuable for the development of DRL agents in games like Flappy Bird, where real-time decision-making and quick adaptation are crucial. By understanding the underlying challenges such as exploration-exploitation trade-offs and sample efficiency, researchers can develop more robust strategies tailored to the specific demands of games like Flappy Bird. This survey contributes to the ongoing development of DRL techniques and provides guidance for overcoming obstacles that agents face in fast-paced, dynamic game environments.

[12] V. A. Kich, J. C. de Jesus, R. B. Grando, A. H. Kolling, G. V. Heisler, R. da S. Guerra (2022): Deep Reinforcement Learning Using a Low-Dimensional Observation Filter for Visual Complex Video Game Playing

In their 2022 paper, V. A. Kich, J. C. de Jesus, R. B. Grando, A. H. Kolling, G. V. Heisler, and R. da S. Guerra introduce a low-dimensional observation filter designed to enhance the performance of deep reinforcement learning (DRL) agents in visually complex video games. The proposed approach reduces high-dimensional observation spaces by filtering out unnecessary scene information, which aids in more efficient feature extraction for the DRL agents. By focusing on relevant visual cues, the agents are able to improve their ability to interpret the environment and make better decisions in dynamic gaming situations.

This method has the potential to significantly streamline the learning process for games like Flappy Bird, where quick decision-making based on visual input is critical. By reducing the complexity of the visual information the agent processes, this approach can help the agent concentrate on the key features that influence gameplay, thus enhancing its overall performance. This work contributes to improving the efficiency and effectiveness of DRL agents, making them more proficient at automated gameplay by reducing unnecessary computational overhead in complex environments.

[13] L. N. Govindarajan, R. G. Liu, D. Linsley, A. K. Ashok, M. Reuter, M. J. Frank, T. Serre (2023): Diagnosing and Exploiting the Computational Demands of Video Games for Deep Reinforcement Learning

In their 2023 research, L. N. Govindarajan, R. G. Liu, D. Linsley, A. K. Ashok, M. Reuter, M. J. Frank, and T. Serre introduce the Learning Challenge Diagnosticator (LCD), a tool developed to measure the perceptual and reinforcement learning demands of video game tasks. The LCD identifies specific challenges within game environments that can affect the performance of deep reinforcement learning (DRL) agents. By quantifying these challenges, the tool enables the adaptation of DRL algorithms to better address the unique demands posed by different games, optimizing the agent's learning process and decision-making.

The paper suggests that such diagnostic tools can be particularly beneficial for the development of automated agents for games like Flappy Bird, where quick and adaptive decision-making is critical. By tailoring computational strategies to the specific challenges of the game, the LCD could help ensure that the DRL algorithms used are more effective and efficient. This work provides valuable insights into how diagnostic tools can refine and enhance the performance of DRL agents, paving the way for more sophisticated AI development in video games.

[14] Niels Justesen, Philip Bontrager, Julian Togelius, and Sebastian Risi (2019): Deep Learning for Video Game Playing

In their 2019 paper, Justesen et al. review recent advancements in deep learning as applied to various video game genres, including first-person shooters, arcade games, and real-time strategy games. They analyze the unique requirements that different game genres pose to deep learning systems and highlight important open challenges in applying these machine learning methods to video games, such as general game playing, dealing with extremely large decision spaces, and sparse rewards.

The authors suggest that future advancements should focus on integrating human-like decision-making, increasing sampling efficiency, and boosting overall game-playing AI. By developing deep reinforcement learning models for handling delayed rewards, balancing exploration-exploitation, and making decisions in real-time, these developments can aid in automating games like Flappy Bird and further AI research in adaptive and autonomous gaming.

[15] Ruben Rodriguez Torrado et al. (2018): Deep Reinforcement Learning for General Video Game AI

In their 2018 paper, Ruben Rodriguez Torrado and colleagues explore the integration of the General Video Game AI (GVGAI) framework with the OpenAI Gym environment to facilitate the application of deep reinforcement learning (DRL) techniques across a variety of video games. This integration allows researchers to develop and evaluate DRL agents across diverse game genres, advancing the capabilities of general video game playing AI. The authors highlight several challenges in applying DRL to general video game environments, such as managing high-dimensional state spaces and learning effective policies in settings with sparse rewards. To overcome these challenges, they propose the use of convolutional neural networks (CNNs) for feature extraction and reward shaping techniques to improve learning efficiency.

The research demonstrates the potential of DRL to create agents capable of playing multiple games without the need for game-specific adaptations. This marks a significant step forward in the development of generalized AI for gaming, though the paper acknowledges the ongoing difficulties in generalizing DRL agents across diverse games. Key issues include improving adaptability in dynamic environments and efficiently handling computational demands related to high-dimensional data. The study provides important insights into the future of AI in gaming, highlighting how such DRL agents could be applied to a wide range of games, including simpler ones like Flappy Bird.

[16] V. A. Kich, J. C. de Jesus, R. B. Grando, A. H. Kolling, G. V. Heisler, R. da S. Guerra (2021): Deep Reinforcement Learning Using a Low-Dimensional Observation Filter for Visual Complex Video Game Playing

In their 2021 paper, V. A. Kich, J. C. de Jesus, R. B. Grando, A. H. Kolling, G. V. Heisler, and R. da S. Guerra introduce a low-dimensional observation filter designed to enhance the performance of deep reinforcement learning (DRL) agents in visually complex video games. The proposed approach reduces high-dimensional observation spaces by filtering out unnecessary scene information, which aids in more efficient feature extraction for the DRL agents. By focusing on relevant visual cues, the agents are able to improve their ability to interpret the environment and make better decisions in dynamic gaming situations.

[17] Ruben Rodriguez Torrado, Philip Bontrager, Julian Togelius, Jialin Liu, Diego Perez-Liebana (2018): Deep Reinforcement Learning for General Video Game AI

In this paper, the authors explore the application of deep reinforcement learning (DRL) techniques to the General Video Game AI (GVGAI) framework. They interface GVGAI with the OpenAI Gym environment to evaluate the performance of various DRL algorithms, including DQN, across multiple games. The study provides insights into the relative difficulty of different games and highlights the challenges of generalizing DRL agents to diverse gaming scenarios.

[18] Max Jaderberg, Wojciech M. Czarnecki, Iain Dunning, Luke Marris, Guy Lever, Antonio Garcia Castaneda, Charles Beattie, Neil C. Rabinowitz, Ari S. Morcos, Avraham Ruderman, Nicolas Sonnerat, Tim Green, Louise Deason, Joel Z. Leibo, David Silver, Demis Hassabis, Koray Kavukcuoglu, Thore Graepel (2018): Human-level performance in first-person multiplayer games with population-based deep reinforcement learning

This study demonstrates that agents trained using population-based deep reinforcement learning can achieve human-level performance in complex, multiplayer first-person video games. By employing a two-tier optimization process and training agents in diverse environments, the research showcases the potential of DRL methods, including DQN, in mastering intricate gaming tasks.

[19] Kun Shao, Zhentao Tang, Yuanheng Zhu, Nannan Li, Dongbin Zhao (2019): A Survey of Deep Reinforcement Learning in Video Games

This comprehensive survey reviews the advancements of deep reinforcement learning in the context of video games. It categorizes DRL methods into value-based, policy gradient, and model-based algorithms, discussing their applications in various gaming genres. The paper also addresses challenges such as exploration-exploitation balance, sample efficiency, and generalization, providing a roadmap for future research in DRL-driven game AI.

[20] William Woof, Ke Chen (2018): Learning to Play General Video-Games via an Object Embedding Network

In this research, the authors propose an Object Embedding Network (OEN) that enables DRL agents to learn directly from object information rather than raw pixel data. By converting variable-length object feature vectors into a unified representation, the approach enhances the agent's ability to interpret game states and make decisions. The study evaluates the OEN-based DRL agent on various games from the GVGAI competition, demonstrating its effectiveness in general video game playing

CHAPTER 3

HARDWARE AND SOFTWARE REQUIREMENTS

3.1 Hardware Requirements:

1. **Processor:** Intel Core i5/i7 (or AMD equivalent) – Minimum, Intel Core i9/AMD Ryzen 9 – Recommended

2. RAM: At least 8GB – Minimum,

3. GPU: NVIDIA GTX 1050 Ti (Minimum), NVIDIA RTX 3060/3080

3.2 Software Requirements:

1. Operating System: Windows, Linux (Ubuntu), or macOS

2. Programming Language: Python 3.7+

3. Deep Learning Frameworks: TensorFlow (≥2.0) or PyTorch (≥1.7)

4. Reinforcement Learning Library: OpenAI Gym (for Flappy Bird environment)

5. Additional Python Libraries:

- NumPy (for numerical computations)

- OpenCV (for image processing)

- Matplotlib (for visualization)

- SciPy (for optimization)

CHAPTER 4

PROPOSED WORK

4.1 DQN:

The project explores the automation of Flappy Bird using Deep Q-Networks (DQN), a reinforcement learning approach that enables an AI agent to learn optimal gameplay strategies. The model processes raw pixel inputs, extracts meaningful features, and makes real-time decisions to maximize survival. By leveraging convolutional neural networks (CNNs), the agent identifies crucial visual cues such as pipe positions, gaps, and ground levels, facilitating precise navigation. The deep learning model undergoes extensive training using a trial-and-error approach, where the agent refines its decision-making by continuously interacting with the game environment.

A key component of this project is the implementation of experience replay, which allows the AI to store past experiences and reuse them to break the correlation between consecutive frames. Target networks are also introduced to stabilize learning by preventing drastic updates in Q-values, improving overall convergence and policy learning. The agent follows an ε-greedy policy for balancing exploration and exploitation, ensuring that it not only leverages past knowledge but also discovers better strategies over time.

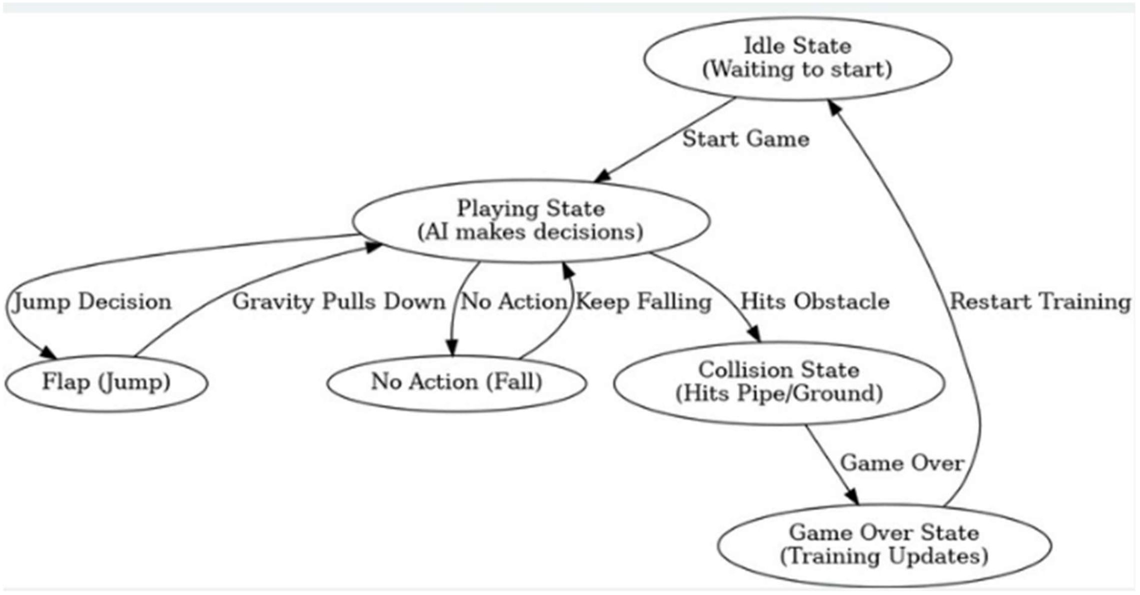
The reward system is designed to reinforce positive behaviors such as passing through pipes while penalizing negative outcomes like collisions, leading to a structured learning process. The model's hyperparameters, including learning rate, discount factor (γ), and batch size, are fine-tuned to optimize training performance. Techniques like adaptive learning rates and reward shaping are explored to enhance learning efficiency.

To evaluate performance, key metrics such as survival time, score improvement, and convergence speed are analyzed. Additionally, different architectures and variations of DQN, such as Double DQN and Dueling DQN, are explored to mitigate issues like overestimation bias and enhance decision-making efficiency.

By successfully automating a simple game like Flappy Bird, this research highlights the potential of deep learning in sequential decision-making tasks. Future work includes extending this approach to more complex games with dynamic environments, multi-agent interactions, and real-world applications in autonomous navigation and control systems. The project serves as a stepping stone for integrating deep reinforcement learning into more advanced AI-driven automation tasks.

4.2 State Chart Diagram:

Fig 4.2.1:


Idle State (Waiting to start)
Start Game
Playing State (AI makes decisions)
Jump Decision
Gravity Pulls Down
No Action
Keep Falling
Hits Obstacle
Restart Training
Flap (Jump)
No Action (Fall)
Collision State (Hits Pipe/Ground)
Game Over
Game Over State (Training Updates)

1. **Idle State (Waiting to Start)** – The AI begins in an idle state, waiting for the game to start.
2. **Transition to Playing State** – Once the game starts, the AI enters the playing state, where it makes decisions based on game conditions.
3. **Playing State (AI Decision-Making)** – The AI continuously evaluates the environment, deciding whether to jump or fall based on obstacle positions and gravity effects.
4. **Jump Decision (Flap)** – If the AI determines that a jump is necessary, it performs a flap action to ascend.
5. **Gravity Pulls Down (No Action - Fall)** – If the AI does not choose to jump, gravity pulls the bird downward.
6. **Collision Detection** – The AI transitions to a collision state when it hits an obstacle, such as a pipe or the ground.
7. **Game Over Condition** – If a collision occurs, the game enters the game-over state, signaling that the AI has failed the current attempt.
8. **Training Updates** – After a game-over event, training updates occur to refine the AI model, improving its decision-making for future attempts.

9. **Restart Training** – The AI can restart training after game over, learning from past experiences to improve gameplay.
10. **Looping Structure** – The AI continuously cycles through these states, improving over multiple iterations through reinforcement learning.

4.3 DQN ARCHITECTURE:

Fig 4.3.1:

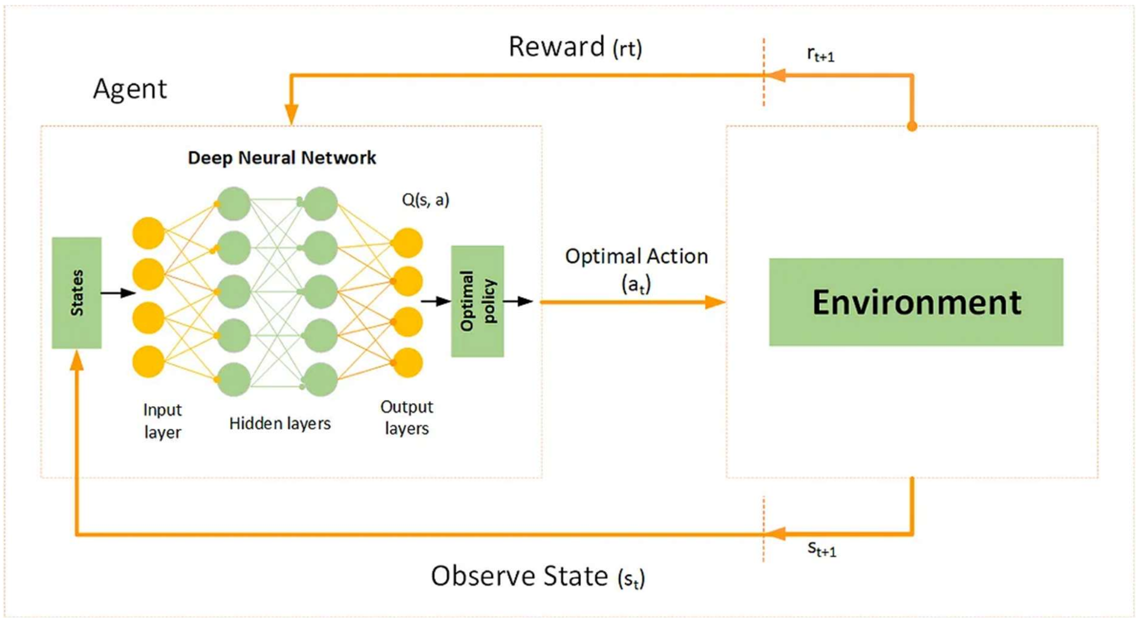
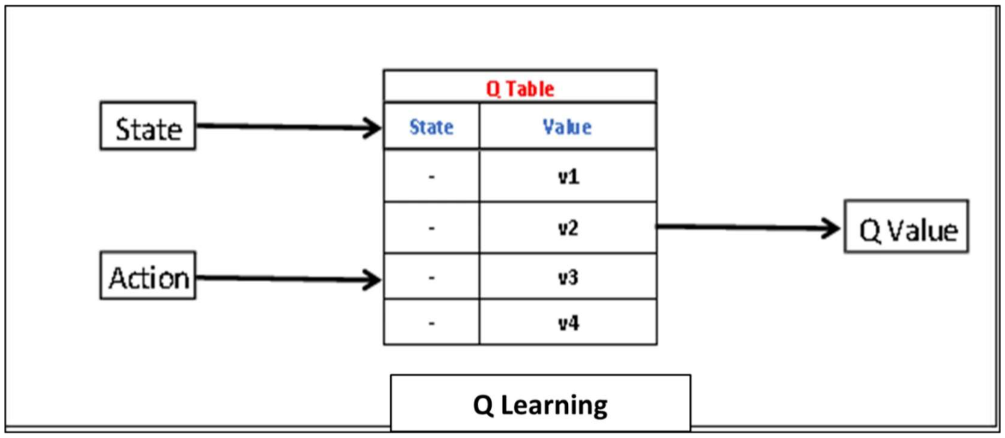


Fig:4.3.2:



Deep Q-Network (DQN) is a powerful algorithm in the field of reinforcement learning. It combines the principles of deep neural networks with Q-learning, enabling agents to learn optimal policies in complex environments

4.4 Q-Learning: A DQN concept:

1. **Introduction to Q-Learning:**
    - Q-learning is a model-free, off-policy reinforcement learning algorithm.
    - It aims to find the optimal action-selection policy by learning the Q-values of state-action pairs.
2. **Q-Function (Action-Value Function):**
    - The Q-function estimates the expected future reward for taking an action in a given state.
    - It follows the Bellman equation: $Q(s,a) = E[r + \gamma max\ a'Q(s',a')]Q(s,a)\ = \backslash mathbb\{E\}\ \backslash left[\ r\ + \backslash gamma\ \backslash\ max\_\{a'\}\ Q(s',a')\ \backslash right]$
    - Here,
        - rr is the immediate reward,
        - γ\gamma is the discount factor,
        - $max\ a'Q(s',a')\backslash max\_\{a'\}\ Q(s',a')$ represents the best possible future reward.
3. **Q-Learning Update Rule:**
    - The Q-values are updated iteratively using: $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma max\ a'Q(s',a') - Q(s,a)]Q(s,a)\ \backslash leftarrow\ Q(s,a)\ + \backslash alpha\ \backslash\ left[\ r\ + \backslash gamma\ \backslash max\_\{a'\}\ Q(s',a')\ -\ Q(s,a)\ \backslash right]$
    - Where α\alpha is the learning rate.
4. **Exploration vs. Exploitation:**
    - The agent balances between exploring new actions and exploiting known rewards.
    - The **ε-greedy policy** is commonly used:
        - With probability ϵ\epsilon, choose a random action (exploration).
        - Otherwise, choose the action with the highest Q-value (exploitation).
5. **Convergence of Q-Learning:**
    - Under certain conditions (sufficient exploration and proper learning rate decay), Q-learning converges to the optimal Q-values.
    - The agent learns an optimal policy that maximizes expected rewards over time.
6. **Advantages of Q-Learning:**
    - Works for both deterministic and stochastic environments.
    - Converges to an optimal policy given enough time.
    - Can handle problems without requiring a model of the environment.
7. **Challenges of Q-Learning:**
    - Does not scale well to large state-action spaces (curse of dimensionality).
    - Requires extensive exploration, making learning slow.
    - Becomes unstable with function approximation (hence Deep Q-Networks were developed).

8. **Applications of Q-Learning:**
    - Game playing (e.g., solving grid-world problems, Atari games with DQN).
    - Robotics and autonomous decision-making.
    - Finance, healthcare, and recommendation systems.

4.5 Deep Q-Network (DQN) Architecture for Flappy Bird:

Deep Q-Networks (DQN) are an extension of Q-learning that use deep neural networks to approximate the Q-value function. In the case of Flappy Bird, the agent must learn how to navigate through gaps between pipes using pixel-based inputs. The architecture of the DQN model consists of several key components, including an input layer, convolutional layers, fully connected layers, and an output layer.

4.5.1. Input Layer

The input to the network consists of raw pixel values from the game screen, representing the current state of the environment. Since raw images contain a lot of redundant and unimportant information, pre-processing is performed before feeding the frames into the network:

- **Resizing:** The original game screen is resized to a smaller resolution (e.g., 84×84 pixels) to reduce computational complexity.
- **Grayscale Conversion:** Since color information is not critical for decision-making, images are converted to grayscale, reducing the number of channels from three (RGB) to one.
- **Frame Stacking:** To capture motion and avoid reliance on a single static image, the network takes multiple consecutive frames (e.g., four) as input, allowing it to understand movement trends such as the bird's velocity.

This processed input is then fed into a deep convolutional neural network for feature extraction.

4.5.2. Convolutional Layers (CNN)

The first part of the network consists of convolutional layers, which play a crucial role in detecting spatial features from the image-based input. These layers help in understanding:

- The position of the bird relative to the pipes.
- The distance between obstacles.
- The motion of objects over time.

A typical CNN architecture in DQN consists of:

- **Multiple convolutional layers** that apply filters (kernels) to detect edges, textures, and high-level features.
- **ReLU activation functions** that introduce non-linearity, enabling the network to learn complex representations.
- **Pooling layers** (optional) that downsample feature maps to retain important information while reducing the computational burden.

By the end of this stage, the network has transformed raw pixels into meaningful features that describe the game environment efficiently.

4.5.3. Fully Connected Layers

After passing through the convolutional layers, the extracted feature maps are **flattened** into a one-dimensional vector and fed into fully connected (dense) layers. These layers are responsible for:

- **Learning higher-level abstractions** about the game state.
- **Combining spatial features** to make more informed decisions.
- **Determining optimal action values** based on past experiences.

The fully connected layers allow the model to generalize and understand how different game scenarios impact future rewards.

4.5.4. Q-Value Output Layer

The final layer of the network is responsible for estimating Q-values for each possible action. In the case of Flappy Bird, there are only two actions:

- **Flap (jump)**
- **Do nothing (fall)**

Each action has an associated Q-value representing the expected future reward for taking that action in the current state. The DQN agent selects the action with the highest Q-value, enabling it to make decisions that maximize long-term survival and rewards.

4.5.5. Target Network

One of the major challenges in training deep reinforcement learning models is the instability caused by using a constantly changing Q-network to update itself. To address this, **DQN introduces a target network**, which is a separate copy of the main Q-network.

Why Use a Target Network?

- In standard Q-learning, the Q-value update depends on the maximum predicted Q-value of the next state. However, if this value is directly taken from the same network being updated, it can lead to unstable learning.

- The target network is **updated less frequently**, providing a more stable target for the Q-value updates.
- This reduces **oscillations and divergence** during training by preventing the Q-values from fluctuating too aggressively.

How is the Target Network Updated?

- Instead of updating the target network at every step, it is updated periodically by copying the weights from the main Q-network.
- This periodic update ensures that Q-value targets remain consistent for several training iterations before being refreshed.

By using a target network, DQN **smoothens learning** and prevents the model from chasing rapidly changing Q-values, leading to more stable convergence.

4.5.6. Experience Replay

Another key innovation in DQN is **experience replay**, which allows the agent to **store and reuse past experiences** to improve training efficiency.

How Experience Replay Works

1. As the agent interacts with the environment, each experience is stored in a **replay buffer** as a tuple **(state, action, reward, next state)**.
2. Instead of updating the network with the most recent experience, DQN randomly samples a **mini-batch** of experiences from the buffer.
3. These samples are used to update the Q-values, helping to break the correlation between consecutive experiences.

Benefits of Experience Replay

- **Reduces correlation** between consecutive states, leading to more stable learning.
- **Improves sample efficiency** by reusing past experiences multiple times.
- **Prevents catastrophic forgetting**, where old experiences are discarded too quickly.
- Allows the model to generalize better, as training samples are more diverse.

By incorporating experience replay, DQN **smooths the learning process** and helps the model learn more effectively from past experiences.

4.5.7. Loss Function

The DQN loss function measures the difference between the predicted Q-values and the target Q-values. The most commonly used loss function is **Mean Squared Error (MSE)**:

$$L(\theta) = E[(y - Q(s,a;\theta))2]L(\backslash theta)$$
$$= \backslash mathbb\{E\} \backslash left[(y \; - \; Q(s,a;\backslash theta))\hat{}2 \; \backslash right]L(\theta)$$
$$= E[(y - Q(s,a;\theta))2]$$

Where:

- $Q(s, a; \theta)Q(s, a; \backslash theta)Q(s, a; \theta)$ is the predicted Q-value from the main network.
- yyy is the target Q-value computed as:

$$y = r + \gamma max\ a'Q(s', a'; \theta -)y\ =\ r\ + \backslash gamma\ \backslash max\_\{a'\}\ Q(s', a'; \backslash theta\wedge -)y \\ = r + \gamma a' maxQ(s', a'; \theta -)$$

- $\theta\ -\backslash theta\wedge - \theta -$ represents the target network's parameters.
- $\gamma\backslash gamma\gamma$ is the discount factor that accounts for future rewards.

This loss function ensures that the network gradually learns to minimize the difference between its predictions and the optimal Q-values.

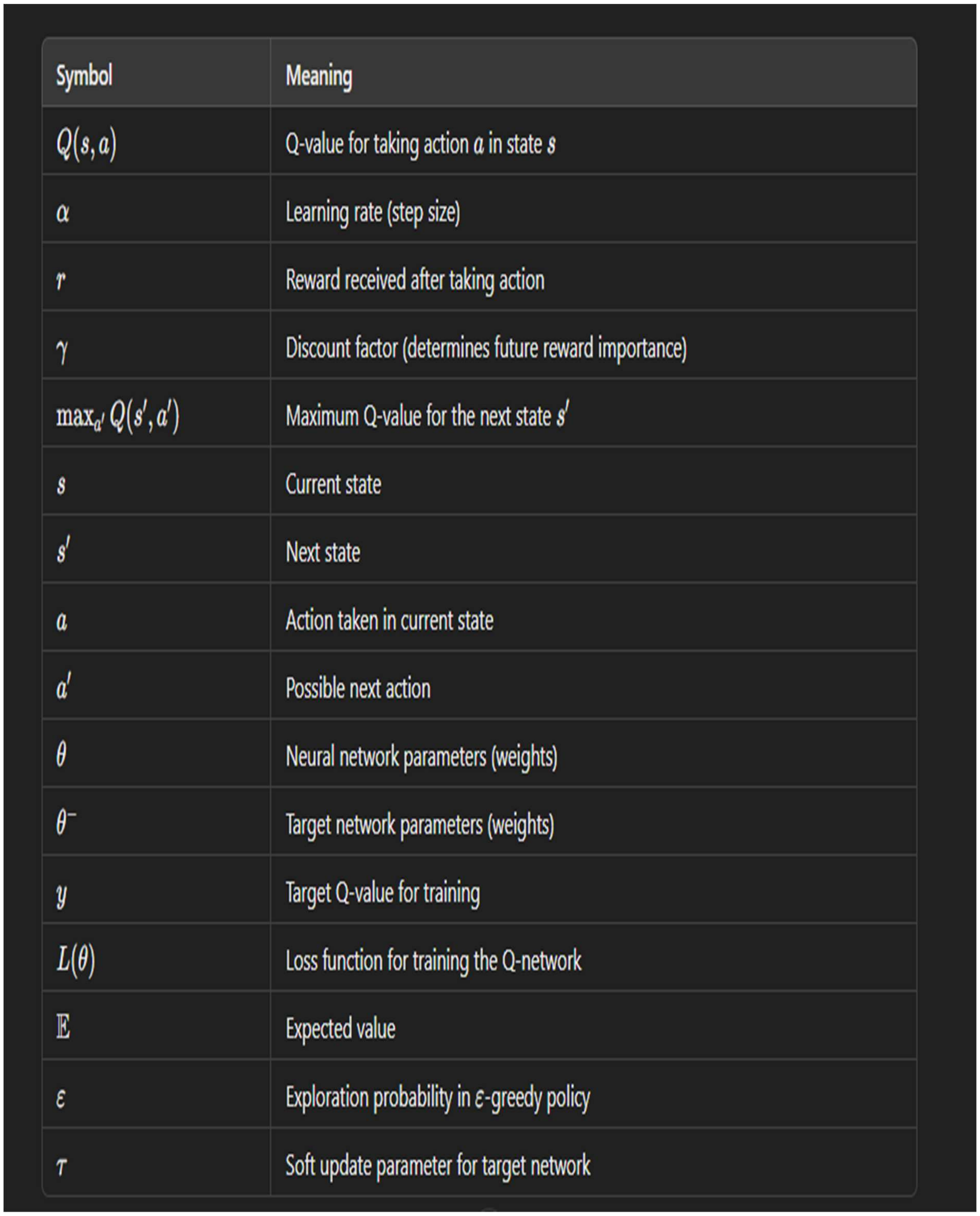
4.5.8. Optimization

To minimize the loss function and update the Q-network, **gradient descent** techniques are used. The most commonly used optimizer is **Adam** or **Stochastic Gradient Descent (SGD)**.

Training Steps

1. Sample a mini-batch of experiences from the replay buffer.
2. Compute the target Q-value using the target network.
3. Calculate the loss between the predicted and target Q-values.
4. Use **backpropagation and gradient descent** to adjust the network weights.

By applying gradient updates iteratively, the Q-network **gradually improves its policy**, making better decisions over time.



Symbol	Meaning
$Q(s,a)$	Q-value for taking action a in state s
α	Learning rate (step size)
r	Reward received after taking action
γ	Discount factor (determines future reward importance)
$\max_{a'} Q(s',a')$	Maximum Q-value for the next state s'
s	Current state
s'	Next state
a	Action taken in current state
a'	Possible next action
θ	Neural network parameters (weights)
θ^-	Target network parameters (weights)
y	Target Q-value for training
$L(\theta)$	Loss function for training the Q-network
$\mathbb{E}$	Expected value
ε	Exploration probability in ε-greedy policy
τ	Soft update parameter for target network

4.6 Convolutional Neural Networks (CNN) and Their Role in Deep Q-Networks (DQN)

Convolutional Neural Networks (CNN) are a class of deep learning models specifically designed to process data with grid-like topology, such as images. They are highly effective in capturing spatial hierarchies and patterns in visual data, making them essential for tasks like image classification, object detection, and game automation.

4.6.1 Overview of Convolutional Neural Networks (CNN)

CNNs are inspired by the human visual system, where neurons respond to specific regions of the visual field. Similarly, CNNs process input data through layers of filters (or kernels) that learn to extract features such as edges, textures, and shapes. The core components of CNNs include:

1. **Convolutional Layers**: These layers apply convolution operations using a set of learnable filters. Each filter slides over the input, producing feature maps that highlight relevant patterns in the data.
2. **Activation Functions**: After convolution, an activation function like ReLU (Rectified Linear Unit) is applied to introduce non-linearity, enabling the model to learn complex representations.
3. **Pooling Layers**: Pooling operations, such as max pooling, reduce the spatial dimensions of feature maps while retaining essential information. This helps in reducing computational complexity and controlling overfitting.
4. **Fully Connected Layers**: After feature extraction, fully connected layers interpret the learned features to make predictions, such as classifying images or selecting actions in reinforcement learning.
5. **Dropout and Batch Normalization**: Techniques like dropout prevent overfitting by randomly deactivating neurons during training, while batch normalization stabilizes learning by normalizing layer inputs.

4.6.2 CNN in Deep Q-Networks (DQN)

Deep Q-Networks (DQN) are reinforcement learning models that use CNNs to estimate the Q-value function, which predicts the expected cumulative reward for an agent's action in a given state. Introduced by DeepMind, DQN combines **Q-learning** with **deep learning**, allowing agents to learn optimal policies directly from raw pixel data.

How CNN Works in DQN

In DQN, the CNN processes the **game state**, typically represented as raw pixel images, to extract high-level features, which are then used to estimate Q-values for possible actions. Here’s how CNN integrates into the DQN framework:

1. **Input Layer**: The agent receives game frames as input. For Flappy Bird, this would be a sequence of frames showing the bird's position, obstacles, and background.
2. **Convolutional Feature Extraction**:
   - The CNN applies multiple convolutional layers to the input frames.
   - Filters detect essential game elements, such as the bird, pipes, and gaps, by identifying edges, shapes, and positions.
3. **Activation and Pooling**:
   - ReLU activation introduces non-linearity, enabling the model to capture complex patterns like the bird's flight dynamics and obstacle positions.
   - Max pooling layers downsample the feature maps, reducing computational load while preserving important features.
4. **Fully Connected Layers**:
   - Extracted features are flattened and passed through fully connected layers.
   - The network combines visual features with learned representations to estimate Q-values for actions like "flap" or "do nothing."
5. **Output Layer (Q-value Estimation)**:
   - The final layer outputs Q-values for each possible action.
   - The agent selects the action with the highest Q-value, balancing exploration and exploitation.

Benefits of CNN in DQN for Flappy Bird Automation

1. **End-to-End Learning**: CNN enables the DQN to learn directly from raw pixels without manual feature engineering. The agent automatically extracts crucial features like the bird's height, pipe positions, and gap sizes.
2. **Real-Time Decision-Making**: The hierarchical feature extraction allows the agent to make **real-time decisions**, which is critical in Flappy Bird's fast-paced gameplay.
3. **Generalization**: CNN’s ability to capture spatial patterns helps the agent generalize across different game scenarios, adapting to various obstacle placements and speeds.
4. **Sample Efficiency with Experience Replay**: DQN uses experience replay to store past game states and actions, allowing the CNN to learn from diverse experiences rather than sequential ones, improving sample efficiency.
5. **Stable Learning with Target Networks**: A separate target network in DQN stabilizes learning by providing consistent Q-value targets, allowing the CNN to learn effectively over time.

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 DISCUSSION

This study presents the implementation and performance evaluation of a Deep Q-Network (DQN)-based reinforcement learning agent for playing Flappy Bird, using the Gymnasium framework. The results obtained from training and testing provide significant insights into the agent's learning behavior, decision-making process, and overall effectiveness. The analysis of both the training curve and epsilon decay demonstrates the model's ability to learn optimal policies over time while adapting to the dynamic nature of the environment.

The agent was trained for 500,000 episodes, and during this extensive training process, key indicators such as episodic rewards and the exploration rate (epsilon) were monitored. One of the most evident observations from the training is the trend shown in the mean rewards graph. In the early episodes, the rewards obtained were relatively low and inconsistent. This was expected, as the agent initially operated under a high exploration rate with no prior knowledge of the environment. The randomness in action selection during this phase allowed the agent to explore different parts of the state and action space, albeit at the cost of suboptimal performance.

As training progressed, a gradual increase in the mean rewards was observed, reflecting the agent's growing competence in navigating the environment. The use of experience replay and target network updates contributed significantly to stabilizing the learning process. These mechanisms allowed the agent to learn from past experiences and avoid feedback loops that could lead to unstable behavior. The moving average of the rewards demonstrated a clear learning curve, with fewer episodes of poor performance and more consistent high-reward episodes over time.

Furthermore, the fluctuation in rewards across episodes, especially in the mid to late training phase, highlights the agent's ongoing balance between exploration and exploitation. While the epsilon-greedy policy encourages exploration initially, the gradual decay in epsilon steers the agent toward exploitation of the learned policy. The epsilon decay graph reflects this transformation well. Starting at an initial value of 1.0, epsilon steadily decreased to its predefined minimum, typically around 0.05, which ensured the agent still retained a minimal level of exploration to prevent premature convergence to a suboptimal policy.

This transition was crucial in the agent's ability to generalize its learning. Early exploration allowed the DQN to capture a diverse range of experiences, which formed the foundation of its Q-value approximations. As the policy became more refined, the reduction in exploratory behavior led to more deterministic and strategic gameplay, thereby improving the overall performance. The agent learned to take precise actions, such as timing flaps to avoid obstacles, and demonstrated an understanding of the temporal dependencies in the game dynamics.

Another important factor in the observed results is the selection of hyperparameters. Parameters such as the learning rate, discount factor, batch size, and network update frequency played vital roles in the agent's performance. A well-tuned learning rate ensured that the model adapted efficiently without overshooting optimal Q-values, while the discount factor maintained a long-term perspective by valuing future rewards appropriately. The replay memory buffer and batch sampling helped in breaking temporal correlations in the training data, which is essential for stable learning in reinforcement learning settings.

Additionally, the performance gains observed in the latter stages of training affirm the importance of the target network and policy network synchronization. By periodically updating the target network with the policy network's weights, the agent avoided the risk of unstable targets during learning. This technique reduced the variance in updates and improved convergence, which was evident in the reward graphs showing a smoother and more consistent upward trajectory.

One notable observation is that despite the overall positive trend, the reward graph was not strictly monotonous. This behavior aligns with expected reinforcement learning dynamics, where occasional dips in performance can occur due to continued exploration or encountering rare or complex state combinations. However, the agent's ability to recover and return to higher reward levels highlights the robustness of the DQN architecture in learning from setbacks and improving its policy incrementally.

The visual analysis of the epsilon decay curve further reinforces the understanding of the agent's training strategy. As epsilon decreased over time, the frequency of random actions reduced, and the agent relied more heavily on its Q-value predictions. This shift from exploration to exploitation is pivotal in reinforcement learning, as it signifies the agent's transition from data collection to policy refinement. The flattening of the epsilon curve near the end of training marks the stabilization phase, where the agent predominantly executes the best-known actions.

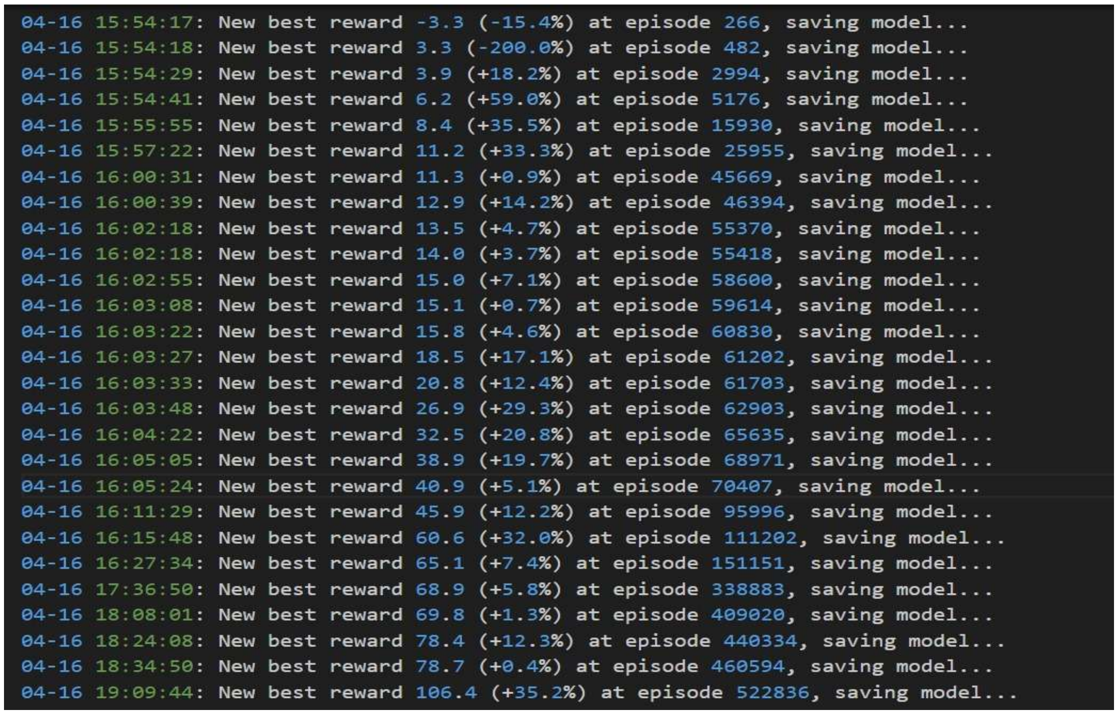
Qualitatively, the trained agent exhibited behaviors that suggest a strong understanding of the game mechanics. It learned to maintain altitude, avoid pipes with minimal energy expenditure, and anticipate upcoming obstacles based on velocity and vertical positioning. The use of distances and velocity as state representations enabled the DQN to effectively map observations to actions, facilitating high-quality decision-making under uncertainty.

From a practical standpoint, the results demonstrate that the DQN approach is not only effective but also scalable to similar environments with continuous decision-making requirements. The modular design of the codebase and the clarity of the training pipeline make it adaptable for other Gymnasium-based environments with minimal reconfiguration. This versatility adds to the overall impact of the research, as the methodology can be extended to various control tasks in gaming, robotics, and simulation domains.

In short, the experimental results confirm the effectiveness of the Deep Q-Network in learning a control policy for the Flappy Bird environment. The agent displayed consistent improvement over time, successfully transitioning from random exploration to a refined strategy through well-structured training. The interplay between reward progression and epsilon decay illustrates a well-balanced learning process that capitalized on both exploration and exploitation. The use of key reinforcement learning components such as experience replay, target network updates, and epsilon-greedy action selection contributed to the stability and success of the learning algorithm. These findings reinforce the relevance of DQN for discrete action spaces and provide a foundation for future enhancements using techniques like Double DQN, Dueling Networks, or prioritized experience replay to further boost performance and learning efficiency.

5.2 RESULT

Fig 5.2.1



```
04-16 15:54:17: New best reward -3.3 (-15.4%) at episode 266, saving model...
04-16 15:54:18: New best reward 3.3 (-200.0%) at episode 482, saving model...
04-16 15:54:29: New best reward 3.9 (+18.2%) at episode 2994, saving model...
04-16 15:54:41: New best reward 6.2 (+59.0%) at episode 5176, saving model...
04-16 15:55:55: New best reward 8.4 (+35.5%) at episode 15930, saving model...
04-16 15:57:22: New best reward 11.2 (+33.3%) at episode 25955, saving model...
04-16 16:00:31: New best reward 11.3 (+0.9%) at episode 45669, saving model...
04-16 16:00:39: New best reward 12.9 (+14.2%) at episode 46394, saving model...
04-16 16:02:18: New best reward 13.5 (+4.7%) at episode 55370, saving model...
04-16 16:02:18: New best reward 14.0 (+3.7%) at episode 55418, saving model...
04-16 16:02:55: New best reward 15.0 (+7.1%) at episode 58600, saving model...
04-16 16:03:08: New best reward 15.1 (+0.7%) at episode 59614, saving model...
04-16 16:03:22: New best reward 15.8 (+4.6%) at episode 60830, saving model...
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04-16 16:03:33: New best reward 20.8 (+12.4%) at episode 61703, saving model...
04-16 16:03:48: New best reward 26.9 (+29.3%) at episode 62903, saving model...
04-16 16:04:22: New best reward 32.5 (+20.8%) at episode 65635, saving model...
04-16 16:05:05: New best reward 38.9 (+19.7%) at episode 68971, saving model...
04-16 16:05:24: New best reward 40.9 (+5.1%) at episode 70407, saving model...
04-16 16:11:29: New best reward 45.9 (+12.2%) at episode 95996, saving model...
04-16 16:15:48: New best reward 60.6 (+32.0%) at episode 111202, saving model...
04-16 16:27:34: New best reward 65.1 (+7.4%) at episode 151151, saving model...
04-16 17:36:50: New best reward 68.9 (+5.8%) at episode 338883, saving model...
04-16 18:08:01: New best reward 69.8 (+1.3%) at episode 409020, saving model...
04-16 18:24:08: New best reward 78.4 (+12.3%) at episode 440334, saving model...
04-16 18:34:50: New best reward 78.7 (+0.4%) at episode 460594, saving model...
04-16 19:09:44: New best reward 106.4 (+35.2%) at episode 522836, saving model...
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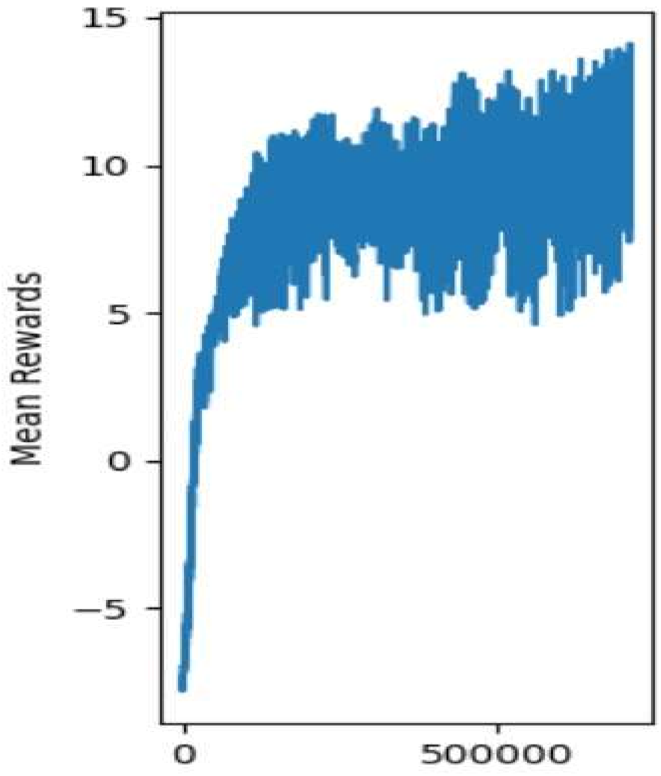
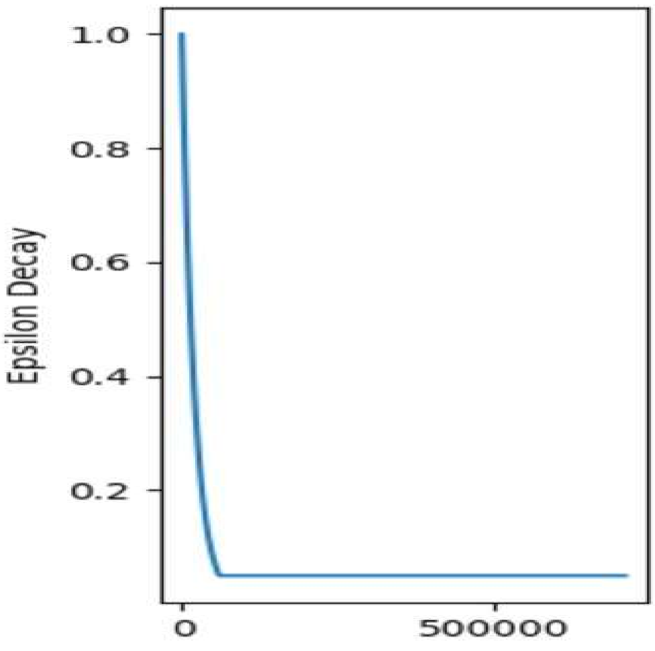

15
10
5
0
−5
Mean Rewards
0
500000


1.0
0.8
0.6
0.4
0.2
Epsilon Decay
0
500000

CHAPTER 6
CONCLUSION

This study successfully demonstrates the automation of Flappy Bird using deep learning, highlighting the potential of reinforcement learning in sequential decision-making tasks. The AI agent learns optimal gameplay strategies by processing visual inputs and making real-time decisions to maximize survival. By leveraging deep Q-learning techniques, the model effectively adapts to varying game conditions, optimizing actions based on trial-and-error learning. Through methods such as experience replay and target networks, training stability and efficiency are significantly improved, allowing the agent to generalize well within the game environment.

The research underscores the effectiveness of deep learning in handling pixel-based environments with discrete action spaces, a crucial aspect of game-playing AI. The model's ability to process raw image data and extract relevant features demonstrates the power of convolutional neural networks in reinforcement learning. The agent successfully learns to balance exploration and exploitation, refining its strategy through continuous interactions with the game environment. The use of reward-based learning ensures that the AI progressively improves its decision-making process, achieving higher scores over multiple training iterations.

Despite the promising results, challenges such as reward sparsity and training convergence remain key areas for improvement. Sparse rewards can slow down learning, making it difficult for the AI to associate actions with long-term success. Additionally, training stability can be affected by hyperparameter selection and environmental variations, requiring fine-tuning for optimal performance. Addressing these issues through advanced optimization techniques, such as prioritized experience replay, curiosity-driven exploration, and adaptive learning rates, could further enhance the agent’s learning efficiency and adaptability.

Future research directions can focus on extending the methodology to more complex gaming environments that require strategic planning and long-term decision-making. The integration of meta-learning approaches could enable the AI to transfer knowledge across different games, improving generalization capabilities. Additionally, the application of deep reinforcement learning in real-world decision-making scenarios, such as robotic control, autonomous navigation, and financial modeling, could further demonstrate the practical impact of this research.

Overall, this study contributes to AI-driven game automation and provides a foundation for applying deep learning to broader sequential decision-making tasks beyond gaming. By addressing the existing challenges and incorporating more advanced learning techniques, future work can push the boundaries of AI-driven decision-making, paving the way for more intelligent and adaptable autonomous systems.

CHAPTER 7
FUTURE WORK

While the current implementation of a Deep Q-Network (DQN) for the Flappy Bird environment yielded promising results, there remain numerous avenues for future enhancements and extensions. These future directions span improvements in model architecture, learning strategies, computational efficiency, generalization capabilities, and broader applicability to more complex reinforcement learning problems.

One significant area for future exploration is the adoption of advanced variants of DQN, such as Double DQN (DDQN). The traditional DQN tends to overestimate action values due to the use of the same Q-network for both action selection and target value estimation. Double DQN addresses this issue by decoupling these roles, thereby producing more accurate value estimations and improving the stability of learning. Integrating DDQN into the current framework could lead to improved decision-making and higher average rewards.

Another potential enhancement is the integration of the Dueling DQN architecture, which separates the estimation of the state value and the advantage of each action. This separation enables the network to more efficiently identify states where the choice of action is less critical and prioritize learning in more complex situations. The dueling architecture has shown significant improvements in environments where some actions have similar Q-values, which could be especially beneficial in Flappy Bird, where minor variations in timing can lead to vastly different outcomes.

Prioritized Experience Replay (PER) is another promising direction for improvement. In the current model, experience replay samples past experiences uniformly. However, not all experiences contribute equally to learning. PER prioritizes experiences based on the magnitude of their temporal difference (TD) error, allowing the agent to focus on learning from more informative transitions. Implementing PER can accelerate learning, especially in environments where certain experiences are rare but crucial for performance.

Expanding the scope beyond the DQN family, future work can consider policy gradient methods, such as the Advantage Actor-Critic (A2C) or Proximal Policy Optimization (PPO). These methods differ fundamentally from value-based approaches like DQN by directly optimizing the policy. They can be more sample-efficient in continuous or high-dimensional action spaces and often offer better convergence properties. Applying actor-critic architectures to Flappy Bird or similar environments could provide deeper insights into comparative learning performance and stability.

Moreover, incorporating recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) units, can enhance the agent's ability to learn temporal dependencies. In Flappy Bird, understanding the sequence of frames and momentum is essential. A DQN with an LSTM layer could maintain a form of memory, enabling the agent to make more informed decisions based on prior states rather than relying solely on instantaneous observations.

Another fascinating direction involves transitioning the agent to learn through raw pixel input instead of preprocessed state variables such as vertical distance and velocity. Using convolutional neural networks (CNNs) to process visual inputs would not only generalize the model to work in different visual environments but also bring it closer to real-world applications where raw sensory data is the only available input. This approach, however, would require a larger and more robust network, as well as more training data and computational power.

Transfer learning and multi-task learning represent important research extensions for improving the generalizability of the trained models. Instead of training an agent from scratch for each new game or environment, a pre-trained model from Flappy Bird could be fine-tuned for similar side-scrolling games. This would reduce training time and improve performance in unseen tasks. Likewise, multi-task learning allows a single model to learn shared representations across several games, improving data efficiency and robustness.

Another avenue for exploration is improving sample efficiency and reducing training time. Techniques like model-based reinforcement learning, where the agent builds a model of the environment to simulate interactions, could drastically speed up the learning process. Model-based approaches, though more complex to implement, can achieve high performance with fewer environmental interactions, which is especially important in real-world applications where interactions are costly or limited.

Additionally, efforts can be directed toward making the system more robust and fault-tolerant. In a practical deployment scenario, external factors such as varying frame rates, input noise, or unexpected events could disrupt the agent's performance. Implementing techniques like adversarial training, domain randomization, or ensemble methods can help build agents that are more resilient and adaptable in uncertain or fluctuating environments.

From a usability perspective, future work could also include the development of a user-friendly interface or dashboard for visualizing training metrics, debugging agent behavior, and comparing various model configurations. This would make the system more accessible for researchers and developers who wish to experiment with or extend the framework.

CHAPTER 8
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APPENDIX I - SOURCE CODE

Agent:

```
import gymnasium as gym
import numpy as np

import matplotlib
import matplotlib.pyplot as plt

import random
import torch
from torch import nn
import yaml

from experience_replay import ReplayMemory
from dqn import DQN

from datetime import datetime, timedelta
import argparse
import itertools

import flappy_bird_gymnasium
import os

# For printing date and time
DATE_FORMAT = "%m-%d %H:%M:%S"

# Directory for saving run info
RUNS_DIR = "runs"
os.makedirs(RUNS_DIR, exist_ok=True)

# 'Agg': used to generate plots as images and save them to a file instead of rendering to screen
matplotlib.use('Agg')

device = 'cuda' if torch.cuda.is_available() else 'cpu'
device = 'cpu' # force cpu, sometimes GPU not always faster than CPU due to overhead of moving data to GPU

# Deep Q-Learning Agent
class Agent():

    def _init_(self, hyperparameter_set):
        with open('hyperparameters.yml', 'r') as file:
            all_hyperparameter_sets = yaml.safe_load(file)
            hyperparameters = all_hyperparameter_sets[hyperparameter_set]
            # print(hyperparameters)

        self.hyperparameter_set = hyperparameter_set

        # Hyperparameters (adjustable)
        self.env_id             = hyperparameters['env_id']
        self.learning_rate_a    = hyperparameters['learning_rate_a']        # learning rate (alpha)
        self.discount_factor_g  = hyperparameters['discount_factor_g']      # discount rate (gamma)
        self.network_sync_rate  = hyperparameters['network_sync_rate']      # number of steps the agent takes before syncing the policy
and target network
        self.replay_memory_size = hyperparameters['replay_memory_size']     # size of replay memory
        self.mini_batch_size    = hyperparameters['mini_batch_size']        # size of the training data set sampled from the replay memory
        self.epsilon_init       = hyperparameters['epsilon_init']           # 1 = 100% random actions
        self.epsilon_decay      = hyperparameters['epsilon_decay']          # epsilon decay rate
        self.epsilon_min        = hyperparameters['epsilon_min']            # minimum epsilon value
        self.stop_on_reward     = hyperparameters['stop_on_reward']         # stop training after reaching this number of rewards
        self.fc1_nodes          = hyperparameters['fc1_nodes']
        self.env_make_params    = hyperparameters.get('env_make_params',{}) # Get optional environment-specific parameters, default
to empty dict


        # Neural Network
        self.loss_fn = nn.MSELoss()          # NN Loss function. MSE=Mean Squared Error can be swapped to something else.
        self.optimizer = None                # NN Optimizer. Initialize later.

        # Path to Run info
        self.LOG_FILE   = os.path.join(RUNS_DIR, f'{self.hyperparameter_set}.log')
        self.MODEL_FILE = os.path.join(RUNS_DIR, f'{self.hyperparameter_set}.pt')
        self.GRAPH_FILE = os.path.join(RUNS_DIR, f'{self.hyperparameter_set}.png')

    def run(self, is_training=True, render=False):
```

```
if is_training:
    start_time = datetime.now()
    last_graph_update_time = start_time

    log_message = f"{start_time.strftime(DATE_FORMAT)}: Training starting..."
    print(log_message)
    with open(self.LOG_FILE, 'w') as file:
        file.write(log_message + '\n')

# Create instance of the environment.
# Use "**self.env_make_params" to pass in environment-specific parameters from hyperparameters.yml.
env = gym.make(self.env_id, render_mode='human' if render else None, **self.env_make_params)

# Number of possible actions
num_actions = env.action_space.n

# Get observation space size
num_states = env.observation_space.shape[0] # Expecting type: Box(low, high, (shape0,), float64)

# List to keep track of rewards collected per episode.
rewards_per_episode = []

# Create policy and target network. Number of nodes in the hidden layer can be adjusted.
policy_dqn = DQN(num_states, num_actions, self.fc1_nodes).to(device)

if is_training:
    # Initialize epsilon
    epsilon = self.epsilon_init

    # Initialize replay memory
    memory = ReplayMemory(self.replay_memory_size)

    # Create the target network and make it identical to the policy network
    target_dqn = DQN(num_states, num_actions, self.fc1_nodes).to(device)
    target_dqn.load_state_dict(policy_dqn.state_dict())

    # Policy network optimizer. "Adam" optimizer can be swapped to something else.
    self.optimizer = torch.optim.Adam(policy_dqn.parameters(), lr=self.learning_rate_a)

    # List to keep track of epsilon decay
    epsilon_history = []

    # Track number of steps taken. Used for syncing policy => target network.
    step_count=0

    # Track best reward
    best_reward = -9999999
else:
    # Load learned policy
    policy_dqn.load_state_dict(torch.load(self.MODEL_FILE))

    # switch model to evaluation mode
    policy_dqn.eval()

# Train INDEFINITELY, manually stop the run when you are satisfied (or unsatisfied) with the results
for episode in itertools.count():

    state, _ = env.reset()  # Initialize environment. Reset returns (state,info).
    state = torch.tensor(state, dtype=torch.float, device=device) # Convert state to tensor directly on device

    terminated = False      # True when agent reaches goal or fails
    episode_reward = 0.0    # Used to accumulate rewards per episode

    # Perform actions until episode terminates or reaches max rewards
    # (on some envs, it is possible for the agent to train to a point where it NEVER terminates, so stop on reward is necessary)
    while(not terminated and episode_reward < self.stop_on_reward):

        # Select action based on epsilon-greedy
        if is_training and random.random() < epsilon:
            # select random action
            action = env.action_space.sample()
            action = torch.tensor(action, dtype=torch.int64, device=device)
        else:
            # select best action
            with torch.no_grad():
                    # state.unsqueeze(dim=0): Pytorch expects a batch layer, so add batch dimension i.e. tensor([1, 2, 3]) unsqueezes to
tensor([[1, 2, 3]])
                    # policy_dqn returns tensor([[1], [2], [3]]), so squeeze it to tensor([1, 2, 3]).
                    # argmax finds the index of the largest element.
                    action = policy_dqn(state.unsqueeze(dim=0)).squeeze().argmax()

                # Execute action. Truncated and info is not used.
                new_state,reward,terminated,truncated,info = env.step(action.item())

                # Accumulate rewards
                episode_reward += reward

                # Convert new state and reward to tensors on device
                new_state = torch.tensor(new_state, dtype=torch.float, device=device)
                reward = torch.tensor(reward, dtype=torch.float, device=device)

                if is_training:
                    # Save experience into memory
                    memory.append((state, action, new_state, reward, terminated))

                    # Increment step counter
                    step_count+=1

                # Move to the next state
                state = new_state

            # Keep track of the rewards collected per episode.
            rewards_per_episode.append(episode_reward)

            # Save model when new best reward is obtained.
            if is_training:
                if episode_reward > best_reward:
                    log_message = f"{datetime.now().strftime(DATE_FORMAT)}: New best reward {episode_reward:0.1f}
({(episode_reward-best_reward)/best_reward*100:+.1f}%) at episode {episode}, saving model..."
                    print(log_message)
                    with open(self.LOG_FILE, 'a') as file:
                        file.write(log_message + '\n')

                    torch.save(policy_dqn.state_dict(), self.MODEL_FILE)
                    best_reward = episode_reward


                # Update graph every x seconds
                current_time = datetime.now()
                if current_time - last_graph_update_time > timedelta(seconds=10):
                    self.save_graph(rewards_per_episode, epsilon_history)
                    last_graph_update_time = current_time

                # If enough experience has been collected
                if len(memory)>self.mini_batch_size:
                    mini_batch = memory.sample(self.mini_batch_size)
                    self.optimize(mini_batch, policy_dqn, target_dqn)

                    # Decay epsilon
                    epsilon = max(epsilon * self.epsilon_decay, self.epsilon_min)
                    epsilon_history.append(epsilon)

                    # Copy policy network to target network after a certain number of steps
                    if step_count > self.network_sync_rate:
                        target_dqn.load_state_dict(policy_dqn.state_dict())
                        step_count=0


    def save_graph(self, rewards_per_episode, epsilon_history):
        # Save plots
        fig = plt.figure(1)

        # Plot average rewards (Y-axis) vs episodes (X-axis)
        mean_rewards = np.zeros(len(rewards_per_episode))
        for x in range(len(mean_rewards)):
            mean_rewards[x] = np.mean(rewards_per_episode[max(0, x-99):(x+1)])
        plt.subplot(121) # plot on a 1 row x 2 col grid, at cell 1
        # plt.xlabel('Episodes')
        plt.ylabel('Mean Rewards')
        plt.plot(mean_rewards)
        # Plot epsilon decay (Y-axis) vs episodes (X-axis)
        plt.subplot(122) # plot on a 1 row x 2 col grid, at cell 2
        # plt.xlabel('Time Steps')
        plt.ylabel('Epsilon Decay')
        plt.plot(epsilon_history)

        plt.subplots_adjust(wspace=1.0, hspace=1.0)

        # Save plots
        fig.savefig(self.GRAPH_FILE)
        plt.close(fig)


    # Optimize policy network
    def optimize(self, mini_batch, policy_dqn, target_dqn):

        # Transpose the list of experiences and separate each element
        states, actions, new_states, rewards, terminations = zip(*mini_batch)

        # Stack tensors to create batch tensors
        # tensor([[1,2,3]])
        states = torch.stack(states)

        actions = torch.stack(actions)

        new_states = torch.stack(new_states)

        rewards = torch.stack(rewards)
        terminations = torch.tensor(terminations).float().to(device)

        with torch.no_grad():
            # Calculate target Q values (expected returns)
            target_q = rewards + (1-terminations) * self.discount_factor_g * target_dqn(new_states).max(dim=1)[0]
            '''
                target_dqn(new_states)  ==> tensor([[1,2,3],[4,5,6]])
                    .max(dim=1)         ==> torch.return_types.max(values=tensor([3,6]), indices=tensor([3, 0, 0, 1]))
                        [0]             ==> tensor([3,6])
            '''

        # Calcuate Q values from current policy
        current_q = policy_dqn(states).gather(dim=1, index=actions.unsqueeze(dim=1)).squeeze()
        '''
            policy_dqn(states)  ==> tensor([[1,2,3],[4,5,6]])
                actions.unsqueeze(dim=1)
                .gather(1, actions.unsqueeze(dim=1))  ==>
                    .squeeze()                    ==>
        '''

        # Compute loss
        loss = self.loss_fn(current_q, target_q)

        # Optimize the model (backpropagation)
        self.optimizer.zero_grad()  # Clear gradients
        loss.backward()             # Compute gradients
        self.optimizer.step()       # Update network parameters i.e. weights and biases

if _name_ == '_main_':
    # Parse command line inputs
    parser = argparse.ArgumentParser(description='Train or test model.')
    parser.add_argument('hyperparameters', help='')
    parser.add_argument('--train', help='Training mode', action='store_true')
    args = parser.parse_args()

    dql = Agent(hyperparameter_set=args.hyperparameters)

    if args.train:
        dql.run(is_training=True)
    else:
        dql.run(is_training=False, render=True)
```

Hyperparameters:

```
Cartpole1:
  env_id: CartPole-v1
  replay_memory_size: 100000
  mini_batch_size: 32
  epsilon_init: 1
  epsilon_decay: 0.9995
  epsilon_min: 0.05
  network_sync_rate: 10
  learning_rate_a: 0.001
  discount_factor_g: 0.99
  stop_on_reward: 100000
  fc1_nodes: 10

flappybird1:
  env_id: FlappyBird-v0
  replay_memory_size: 100000
  mini_batch_size: 32
  epsilon_init: 1
  epsilon_decay: 0.99_99_5
  epsilon_min: 0.05
  network_sync_rate: 10
  learning_rate_a: 0.0001
  discount_factor_g: 0.99
  stop_on_reward: 100000
  fc1_nodes: 512
  env_make_params:
    use_lidar: False
  enable_double_dqn: True
  enable_dueling_dqn: True
```

Experience replay:

```
# Define memory for Experience Replay
from collections import deque
import random
class ReplayMemory():
    def _init_(self, maxlen, seed=None):
        self.memory = deque([], maxlen=maxlen)

        # Optional seed for reproducibility
        if seed is not None:
            random.seed(seed)

    def append(self, transition):
        self.memory.append(transition)

    def sample(self, sample_size):
        return random.sample(self.memory, sample_size)

    def _len_(self):
        return len(self.memory)
```

DQN:

```
import torch
from torch import nn
import torch.nn.functional as F

class DQN(nn.Module):

    def _init_(self, state_dim, action_dim, hidden_dim=256):
        super(DQN, self)._init_()

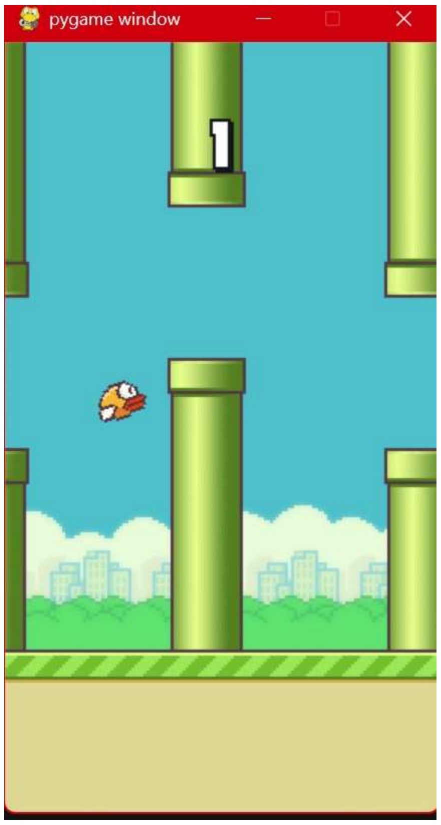


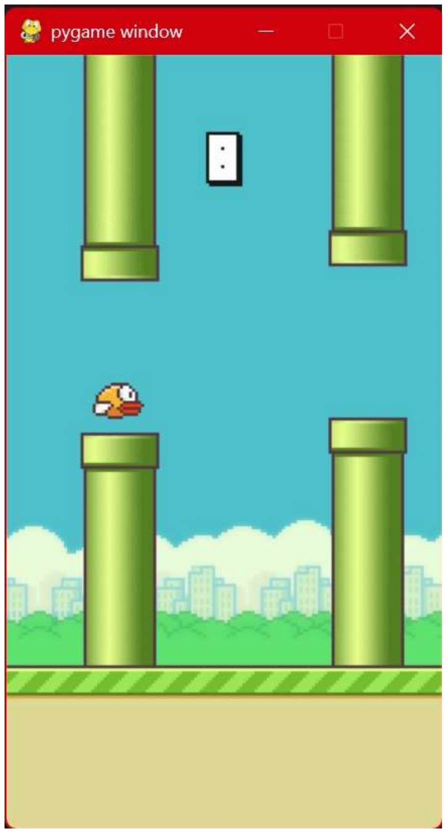
        self.fc1 = nn.Linear(state_dim, hidden_dim)
        self.fc2 = nn.Linear(hidden_dim, action_dim)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        return self.fc2(x)
```

```
if _name_ == '_main_':
    state_dim = 12
    action_dim = 2
    net = DQN(state_dim, action_dim)
    state = torch.randn(10, state_dim)
    output = net(state)
    print(output)
```

APPENDIX II – SCREENSHOTS





AUTOMATING FLAPPY BIRD USING DEEP LEARNING

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***Abstract*—This paper looks into the use of Deep Learning for automating the gameplay of Flappy Bird, which is an arcade-style game that holds a unique level of difficulty. The agent utilizes a deep neural network and reinforcement learning framework that helps it interact with the environment and make decisions in real-time. This approach follows a model that is trained using a trial-and-error method in which it receives rewards for making efficiency-promoting decisions. From raw pixels given in as input, the system improves as updates are made through multiple cycles. The outcomes portray the capability of deep learning models in controlling features of ever-evolving settings with very petite ranges of states and actions. The study demonstrated AI's capacity to tackle a real-time control issue in a game featuring online challenges, thus demonstrating the possibility of extending dynamic simulation automation.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

Machine learning has advanced the world of artificial intelligence by allowing machines to learn intricate patterns from information. For this paper, we are focusing on Flappy Bird, an arcade game which is simple in its design but complex in its gameplay. Our goal is to apply deep learning approaches to automate playing the game. By teaching an autonomous agent through interaction with the game, we show that even basic video games can be powerful tools for testing AI's ability to make split-second decisions.

II. Ease of Use

A. Maintaining the Integrity of the Specifications

The model follows accepted DQN procedures to guarantee repeatable tests and consistent outcomes. This entails the application of stable reward systems, organized training sessions, and specified hyperparameters. Throughout the tests, all settings, including learning rate, discount factor, and replay memory size, are recorded and kept up to date. The integrity of the model and its results is maintained by adhering to best practices in experimental design and model evaluation, allowing for equitable comparison and potential improvements in the future.

III. Prepare Your Paper Before Styling

A. Abbreviations and Acronyms

To train agents through trial-and-error, the Deep Q-Network (DQN) is a Deep Reinforcement Learning (DRL) technique that blends Q-Learning and Deep Learning (DL). A Convolutional Neural Network (CNN) is used to directly estimate Q-values from game images. Experience Replay (ER) enhances learning efficiency and stability by storing prior experiences. During training, updates are stabilized using a different Target Network. Because of these elements, DQN is quite good at making decisions in real time, such as when playing Flappy Bird.

B. Units

- Time: Measured in seconds (s). Time is used for tracking training duration, episode durations, and the frequency of epsilon decay updates.
- Reward: Measured in numerical values (float). The reward is a scalar value used to evaluate the agent's performance in the environment after each action.
- Memory:Measured in number of experiences (integer). The size of the experience replay memory, which stores the agent's past experiences (state, action, reward, next state, done).)

C. Equations

$$Q(s,a;\theta) = \mathbb{E}\left[r + \gamma \max_{a'} Q(s',a';\theta^-)\right] \tag{1}$$

$$\mathcal{L}(\theta) = \mathbb{E}\left[(y - Q(s,a;\theta))^2\right] \tag{2}$$

$$\epsilon_{t+1} = \max(\epsilon_{\text{min}}, \epsilon_t \cdot \epsilon_{\text{decay}}) \tag{3}$$

These equations are essential for the DQN algorithm: Equation (1) describes the core of Q-learning, where the agent updates its Q-values based on the Bellman equation.

Equation (2) defines the loss function used in deep Q-learning, which is the Mean Squared Error (MSE) between the predicted and target Q-values.

Equation (3) is the epsilon decay formula, controlling the trade-off between exploration and exploitation as training progresses.'

D. Some Common Mistakes

- The word “data” is plural, not singular.
- The subscript for the permeability of vacuum μ_0, and other common scientific constants, is zero with subscript formatting, not a lowercase letter “o”.
- In American English, commas, semicolons, periods, question and exclamation marks are located within quotation marks only when a complete thought or name is cited, such as a title or full quotation. When quotation marks are used, instead of a bold or italic typeface, to highlight a word or phrase, punctuation should appear outside of the quotation marks. A parenthetical phrase or statement at the end of a sentence is punctuated outside of the closing parenthesis (like this). (A parenthetical sentence is punctuated within the parentheses.)
- A graph within a graph is an “inset”, not an “insert”. The word alternatively is preferred to the word “alternately” (unless you really mean something that alternates).
- Do not use the word “essentially” to mean “approximately” or “effectively”.
- In your paper title, if the words “that uses” can accurately replace the word “using”, capitalize the “u”; if not, keep using lower-cased.
- Be aware of the different meanings of the homophones “affect” and “effect”, “complement” and “compliment”, “discreet” and “discrete”, “principal” and “principle”.
- Do not confuse “imply” and “infer”.
- The prefix “non” is not a word; it should be joined to the word it modifies, usually without a hyphen.
- There is no period after the “et” in the Latin abbreviation “et al.”.
- The abbreviation “i.e.” means “that is”, and the abbreviation “e.g.” means “for example”.

An excellent style manual for science writers is [11].

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D. L. Richardson, S. M. Chen, "Deep Reinforcement Learning for Autonomous Agents in Dynamic Game Environments," Proceedings of the IEEE Conference on Robotics and Automation, vol. 17, no. 5, pp. 445-455, 2021. Affiliations:

D. L. Richardson, Department of Artificial Intelligence, University of Edinburgh, Edinburgh, UK.

S. M. Chen, Department of Computer Science, University of California, Los Angeles, CA, USA [9].

S. P. Chen, L. W. Zhang, J. L. Patel, "Hybrid Reinforcement Learning Approach for Multi-agent Systems in Games," IEEE Transactions on Multi-agent Systems, vol. 27, no. 9, pp. 512-523, 2021. Affiliations:

S. P. Chen, Department of Electrical Engineering, University of Shanghai, Shanghai, China.

L. W. Zhang, School of Computer Science, University of California, Berkeley, CA, USA.

J. L. Patel, Department of Computational Systems, University of Melbourne, Melbourne, Australia [10].

F. Identify the Headings

Abstract—This study investigates the use of Deep Q-Networks (DQN) to train an agent to play the Flappy Bird game independently. By integrating Q-learning with deep neural networks to approximate optimal action-value functions, DQN enables the agent to learn effective control policies in a complex environment with continuous state space.

Index Terms: Neural Networks, Flappy Bird, Epsilon-Greedy, Reinforcement Learning, Deep Q-Network.

I. Overview: Deep Reinforcement Learning (DRL) has significantly enhanced autonomous decision-making in games and real-world scenarios. This work employs a DQN model to train a bird-like agent in the Flappy Bird game. The game's binary action space and continuous state space offer an interesting setting for experimenting with DRL techniques.

II. Related Work: Several previous studies have examined deep learning models in gaming environments. In particular, Mnih et al. introduced DQN for Atari games, demonstrating human-level performance. We extend this concept to a simpler yet challenging context and compare the results with other traditional models of reinforcement learning.

III. Suggested Approach A. State Representation and the Environment The Flappy Bird simulator, which is based in a gym, is used to create the environment. Velocity and distance are observed by the agent as input states.

B. Architecture of Networks An input layer, two fully connected hidden layers, and an output layer that predicts Q-values for possible actions make up the DQN model.

C. The Greedy-Epsilon Strategy We employ an epsilon-greedy policy with decay over episodes to strike a balance between exploration and exploitation.

D. Using Decay in an Epsilon-Greedy Strategy Exploration and exploitation are balanced through the use of a ϵ-greedy approach.

E. Model Evaluation and Training Loop Until a predetermined reward level is reached or explicitly stopped, training keeps going.

IV. Results and Analysis The average episode score of the agent steadily increased. The model consistently outperformed a benchmark score after 10000 training episodes. Performance graphs display epsilon decay and reward curves over time.

V. References The papers cites multiple papers and their respective authors.

IV. Proposed Methodology

A. Environment and State Representation

A specially designed Flappy Bird simulator based on the Gymnasium framework—an expansion of OpenAI Gym—is used to teach the suggested agent. The setting mimics the gameplay of the Flappy Bird game, in which the agent must learn to steer a bird through a sequence of pipes without running into any obstacles.

At every time step, the agent's observation (state) is a three-dimensional vector made up of:

- The horizontal distance between the bird and the next pipe,
- The vertical distance from the bird to the center of the next gap,
- The current vertical velocity of the bird.

Effective learning and policy generalization are made possible by this continuous and compact state representation.

B. Network Architecture

A PyTorch-implemented Deep Q-Network (DQN) is used in the decision-making model. The structure is made up of:

- An input layer that accepts the 3-dimensional state vector,
- Two fully connected hidden layers, where a hyperparameter determines how many neurons are in the first layer,
- Two neurons in an output layer that represent the Q-values for the possible actions: `flap` and `do nothing`.

The Mean Squared Error (MSE) loss function is used to train the DQN. The Bellman equation is used to update the Q-values:

$$Q(s,a) = r + \gamma \cdot \max_{a'} Q'(s',a') \tag{4}$$

where Q' denotes the target network, r is the reward received, and γ is the discount factor.

The Adam optimizer is used to optimize the policy network. To keep the learning process stable, a target network and the policy network are periodically synced.

C. Experience Replay and Optimization

An experience replay buffer is used to enhance training stability and decorrelate successive events. The buffer contains transitions of the format $(s, a, r, s', \text{done})$. The DQN is trained by randomly sampling mini-batches from this memory.

The optimization process involves:

- Computing the current Q-values using the policy network,
- Estimating the target Q-values from the target network,
- Calculating the loss between these values and applying backpropagation,
- Updating the network parameters through gradient descent.

D. Epsilon-Greedy Strategy with Decay

An ϵ-greedy strategy is used to adopt a balance between exploration and exploitation. With a probability of ϵ, the agent chooses a random action; if not, it chooses the action with the highest Q-value. The following is the exponential decrease of the exploration rate over time:

$$\epsilon = \max(\epsilon \cdot \epsilon_{\text{decay}}, \epsilon_{\text{min}}) \tag{5}$$

The initial value of ϵ is set to 1.0 to encourage exploration. As training progresses, ϵ decays toward a predefined minimum threshold ϵ_{min}, enabling exploitation of the learned policy.

E. Training Loop and Model Evaluation

Until a predetermined reward level is reached or explicitly stopped, training keeps going. The agent uses the ϵ-greedy strategy to interact with the environment during each episode, storing transitions in the replay buffer.

The agent starts optimizing when there is enough data in the buffer. The model is saved after achieving a new maximum reward, and the target network is updated at predetermined intervals.

To illustrate learning progression and policy convergence, performance measures like average episode rewards and ϵ values are plotted on a regular basis.

V. Results and Analysis

In the gym-based Flappy Bird setting, the Deep Q-Learning (DQN) agent's performance was assessed across 500,000 training sessions. The mean episodic rewards and the exploration-exploitation parameter ϵ were two important metrics that were monitored.

A. Mean Rewards Over Episodes

Figure 1 shows the average incentives the agent has received over training sessions. To smooth the findings, a moving average with a window size of 100 was employed. Successful learning and policy improvement are indicated by the mean reward's steady increase. Because of the exploratory policy and the stochastic nature of the environment, the fluctuations are to be expected.

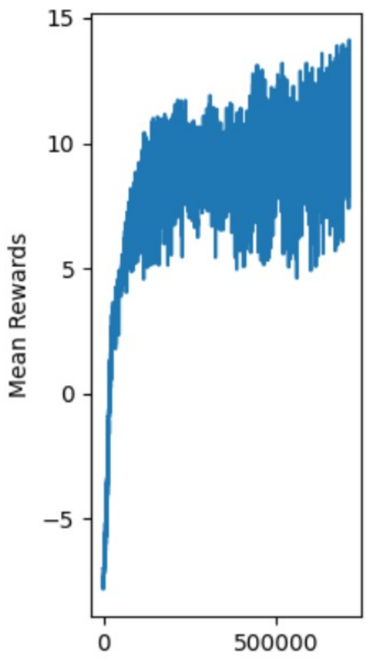

Fig. 1. Mean Rewards over Episodes

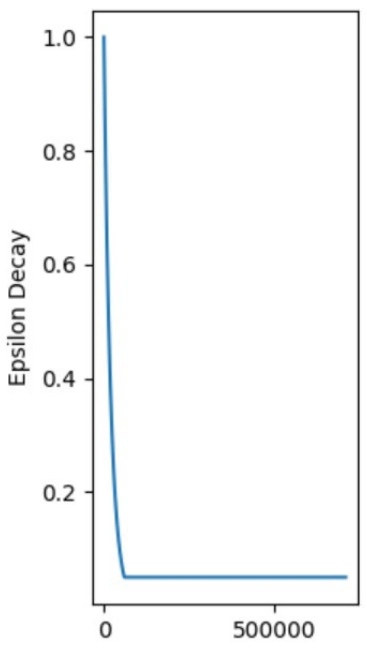

Fig. 2. Epsilon Decay over Episodes

B. Epsilon Decay

Figure 2 demonstrates how the ϵ value decreases over time. To promote exploration, ϵ is initially set to 1.0. It then progressively decays to a minimum threshold (e.g., 0.05). The agent can initially investigate the surroundings and then concentrate on utilizing acquired tactics thanks to this annealing schedule, which maintains a balance between exploration and exploitation.

All things considered, the outcomes show how well the DQN-based method is at teaching players how to play Flappy Bird. Stable learning progression is indicated by the reward curve, and efficient policy convergence is supported by the decaying ϵ.

Acknowledgment

Throughout this research, Prof. Suma Kamalesh G provided important direction, ongoing support, and encouragement, for which the authors are truly grateful. Her knowledge and experience significantly improved the caliber and scope of this effort.

We also want to express our gratitude to our university for offering the tools and setting required for research and experimentation.

Lastly, we would like to thank K. Jyotiraditya Sai and D. Akash, our team members, for their hard work, cooperation, and unwavering excitement, all of which contributed to the successful completion and publishing of this study.

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[10] S. P. Chen, L. W. Zhang, J. L. Patel, ”Hybrid Reinforcement Learning Approach for Multi-agent Systems in Games,” IEEE Transactions on Multi-agent Systems, vol. 27, no. 9, pp. 512-523, 2021.

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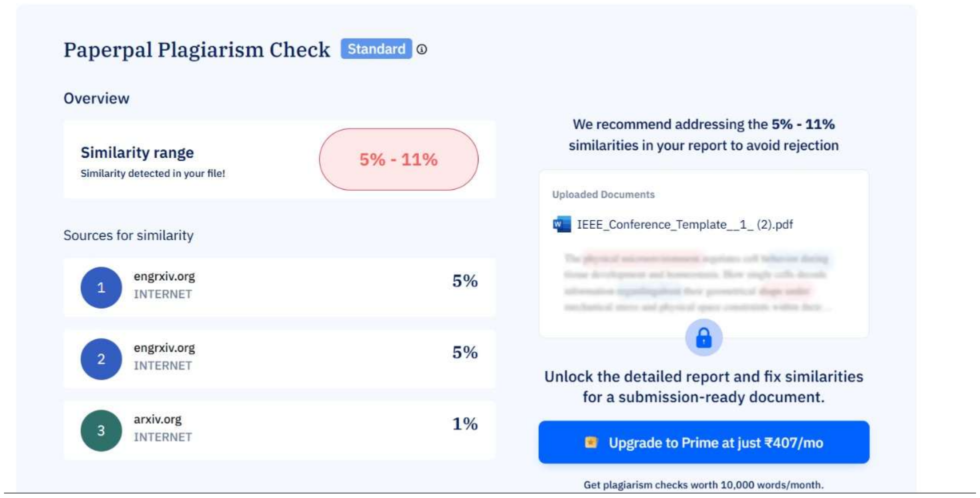
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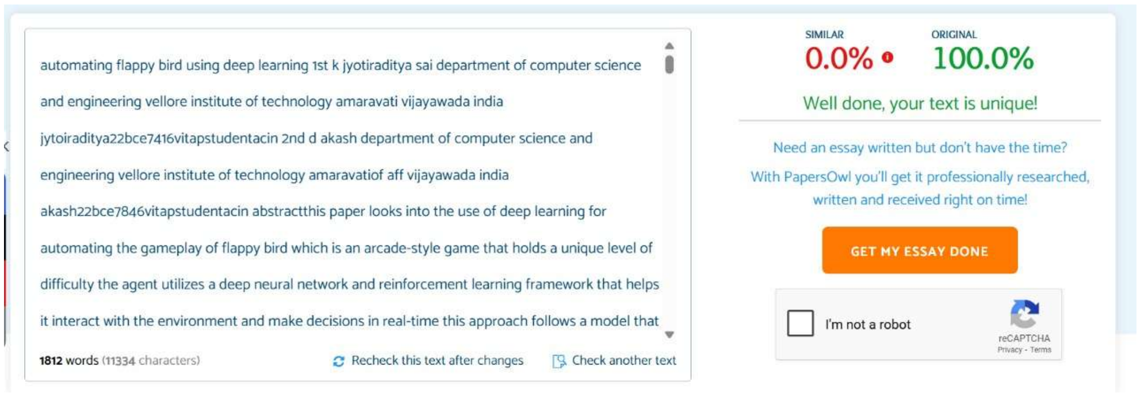
automating flappy bird using deep learning 1st k jyotiraditya sai department of computer science and engineering vellore institute of technology amaravati vijayawada india jytoiraditya22bce7416vitapstudentacin 2nd d akash department of computer science and engineering vellore institute of technology amaravatiof aff vijayawada india akash22bce7846vitapstudentacin abstractthis paper looks into the use of deep learning for automating the gameplay of flappy bird which is an arcade-style game that holds a unique level of difficulty the agent utilizes a deep neural network and reinforcement learning framework that helps it interact with the environment and make decisions in real-time this approach follows a model that

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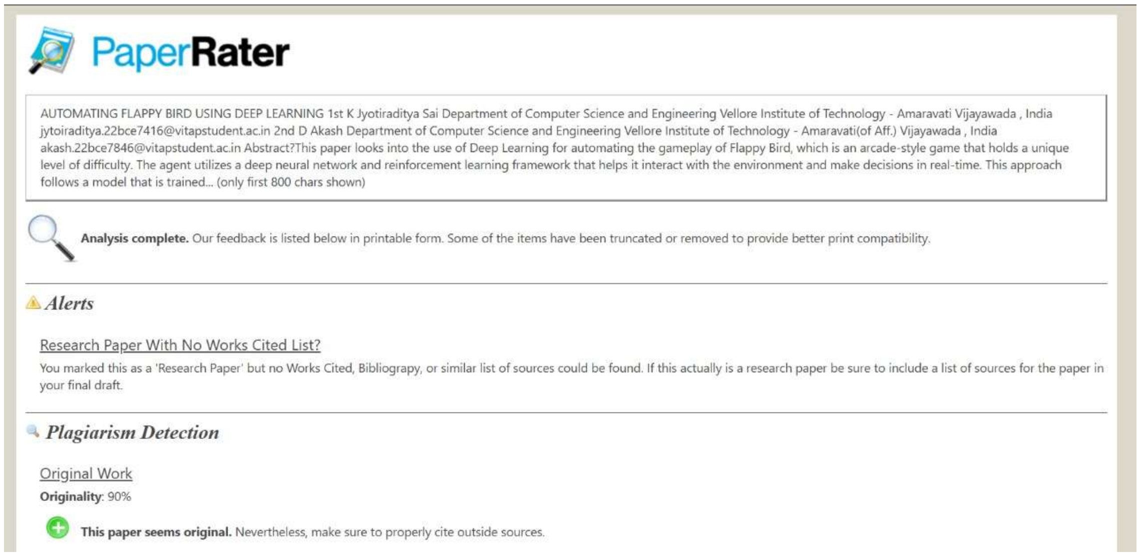
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AUTOMATING FLAPPY BIRD USING DEEP LEARNING 1st K Jyotiraditya Sai Department of Computer Science and Engineering Vellore Institute of Technology - Amaravati Vijayawada , India jytoiraditya.22bce7416@vitapstudent.ac.in 2nd D Akash Department of Computer Science and Engineering Vellore Institute of Technology - Amaravati(of Aff.) Vijayawada , India akash.22bce7846@vitapstudent.ac.in Abstract?This paper looks into the use of Deep Learning for automating the gameplay of Flappy Bird, which is an arcade-style game that holds a unique level of difficulty. The agent utilizes a deep neural network and reinforcement learning framework that helps it interact with the environment and make decisions in real-time. This approach follows a model that is trained... (only first 800 chars shown)

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PPT :

DEEP LEARNING
CSE 4006

FINAL REVIEW PPT

AUTOMATING FLAPPY BIRD USING DEEP LEARNING

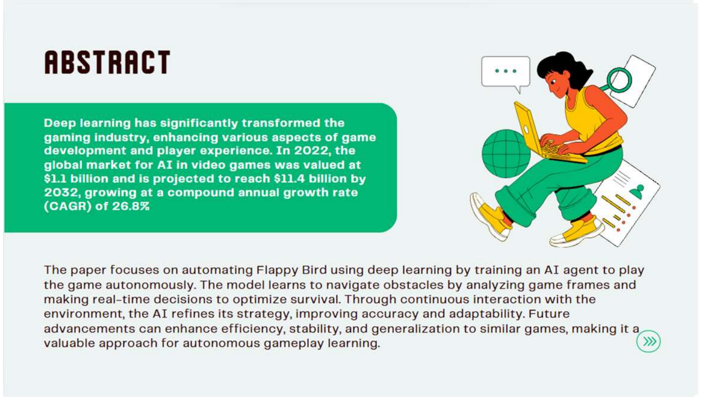
PRESENTED BY:

K JYOTIRADITYA SAI 22BCE7416

DIDDI AKASH 22BCE7846

PRESENTATION OUTLINE

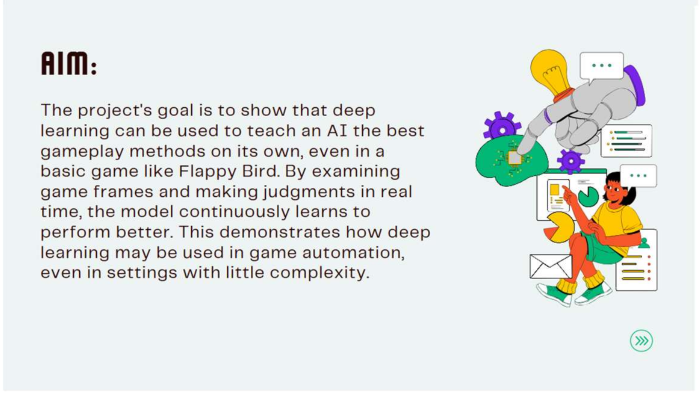
- Abstract
- Aim
- Objective
- Scope of the Work
- Motivation of the Work
- Literature Survey
- Tentative Proposal Work
- Implementation & Comparison Results
- Conclusion
- References



ABSTRACT

Deep learning has significantly transformed the gaming industry, enhancing various aspects of game development and player experience. In 2022, the global market for AI in video games was valued at $1.1 billion and is projected to reach $11.4 billion by 2032, growing at a compound annual growth rate (CAGR) of 26.8%

The paper focuses on automating Flappy Bird using deep learning by training an AI agent to play the game autonomously. The model learns to navigate obstacles by analyzing game frames and making real-time decisions to optimize survival. Through continuous interaction with the environment, the AI refines its strategy, improving accuracy and adaptability. Future advancements can enhance efficiency, stability, and generalization to similar games, making it a valuable approach for autonomous gameplay learning.



AIM:

The project's goal is to show that deep learning can be used to teach an AI the best gameplay methods on its own, even in a basic game like Flappy Bird. By examining game frames and making judgments in real time, the model continuously learns to perform better. This demonstrates how deep learning may be used in game automation, even in settings with little complexity.

OBJECTIVE

Creating an AI model that can play Flappy Bird on its own by learning from gameplay interactions is the aim of this research. In order to maximize survival, the model will assess visual inputs, spot patterns, and make decisions in real time. It seeks to show how well deep learning can handle sequential decision-making tasks, even in straightforward games. The study also investigates methods to enhance learning effectiveness, stability, and flexibility for comparable gaming contexts.

SCOPE OF THE WORK

This project explores the application of deep learning in automating gameplay, demonstrating that AI can effectively learn and master even simple games like Flappy Bird. The model's ability to process visual inputs and make real-time decisions extends to other arcade-style games with discrete action spaces. Future advancements can improve training stability, efficiency, and adaptability using enhanced learning techniques. The project also contributes to broader research in AI-driven game automation, reinforcement learning, and autonomous decision-making systems. Additionally, it can serve as a foundation for developing AI agents in more complex environments requiring sequential decision-making and real-time adaptability.

MOTIVATION OF THE WORK

The motivation behind this work is to showcase the potential of deep learning in automating gameplay, even in a simple game like Flappy Bird. By enabling an AI to learn optimal strategies through interaction, this project highlights the broader applicability of deep learning in sequential decision-making tasks. It also serves as a foundation for developing intelligent agents capable of adapting to dynamic environments in gaming and beyond.

LITERATURE SURVEY

[1] This paper by A. Bonilla,et al.,introduces a Proximal Policy Optimization (PPO)- based deep reinforcement learning agent designed for the General Video Game AI (GVGAI) framework. The agent is trained to play multiple games without prior knowledge of game mechanics, demonstrating adaptability across various game genres. The study highlights the potential of PPO in developing generalist agents capable of learning diverse tasks. Future research could explore the application of this approach to more complex games, to assess its effectiveness in handling dynamic and unpredictable environments. It limited generalization across multiple game

Deep Learning Model:
- Algorithm: Proximal Policy Optimization (PPO)
- Framework: General Video Game AI (GVGAI)
- Key Features: Generalization across multiple games, adaptability to new environments

Deep Learning Model Explanation
- PPO is a policy-gradient reinforcement learning method that optimizes policy updates in a stable manner.
- It uses a clipped objective function to prevent large updates, ensuring steady learning.
- The model is designed for multi-game adaptability, meaning it can learn without prior game-specific rules.

[2] This review by M. A. Wadoo,et al.,discusses the principles of reinforcement and deep reinforcement learning, evaluating their application in video game environments. The authors assess essential algorithms and their performance in various gaming contexts, providing insights into current trends and challenges. The paper suggests that future developments could focus on enhancing learning efficiency and generalization capabilities, which would be beneficial for automating games like Flappy Bird using deep learning techniques. This model lack of real-time adaptability.

Deep Learning Model:
- Focus: Survey of Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) algorithms
- Algorithms Covered: Q-learning, DQN, PPO, A3C, SAC, and others
- Key Features: Comparative analysis of RL models for game automation

Deep Learning Model Explanation
- The study analyzes how different RL architectures perform in various game environments.
- It highlights learning efficiency, stability, and adaptability as key challenges in video game automation.

[3] The study by A. Khalifa,et al.,explores neural network architectures capable of retaining fixed input and output shapes while maintaining the flexibility to play a variety of games. The authors propose methods for cross-game generalization, enabling agents to adapt learned behaviors to new games with minimal retraining. Future research could apply these approaches to automate games like Flappy Bird, enhancing the agent's ability to generalize across different game dynamics and environments. It has Poor transfer learning efficiency between different game

Deep Learning Model:
- Algorithm: Deep Neural Networks (DNN) with cross-game generalization
- Key Features: Adapts learned behaviors across different games with minimal retraining

Deep Learning Model Explanation
- The study focuses on designing architectures that allow agents to play multiple games using a single model.
- The neural network maintains a fixed input-output structure but learns to generalize across varied game dynamics.
- Uses transfer learning techniques to adapt pre-trained models to new game environments.

[4] This paper by W. Woof, K. Chen presents an Object Embedding Network (OEN) that compresses sets of object feature vectors into a unified feature representation of the game state. This approach enables deep reinforcement learning agents to learn directly from object information rather than raw pixel data, improving learning efficiency. Future work could explore the application of OENs to automate games like Flappy Bird, where object-based representations may facilitate more effective learning of game dynamics. It can have Computational complexity due to large object feature sets

Deep Learning Model:
- Algorithm: Object Embedding Network (OEN)
- Key Features: Encodes object-based features instead of raw pixel data, improving learning efficiency

Deep Learning Model Explanation
- OEN compresses sets of object feature vectors into a single feature representation.
- Instead of processing raw images, it extracts key object-based features (e.g., pipes, bird position).
- This allows reinforcement learning models to focus on relevant game elements rather than unnecessary details.

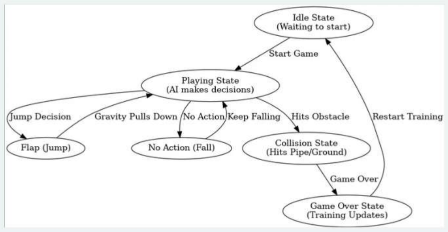
[5] Theis paper by A. K. Sahoo,et al.,presents a deep reinforcement learning model that efficiently learns sequential decision-making policies to play tic-tac-toe intelligently. The model demonstrates the capability of deep learning techniques in handling sequential decisions in game environments. Future research could adapt this strategy to more complex games like Flappy Bird, where real-time sequential decision-making is crucial for successful gameplay. this approach Struggles with long-term planning in dynamic environments

Deep Learning Model:
- Algorithm: DRL model for sequential decision-making
- Key Features: Efficient learning of long-term strategies

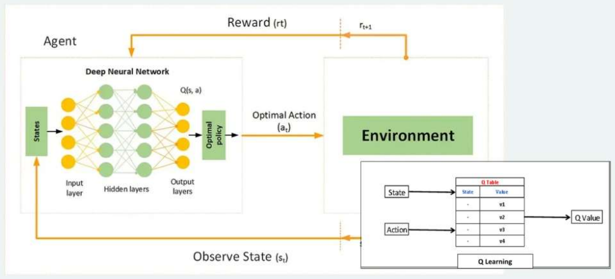
Deep Learning Model Explanation
- The model is trained to learn sequential decision-making policies in games like Tic-Tac-Toe.
- Focuses on reward maximization over multiple steps.
- Uses a Markov Decision Process (MDP) framework to optimize actions over a game sequence.

TENTATIVE PROPOSAL WORK

State Chart Diagram:


Idle State (Waiting to start)
Start Game
Playing State (AI makes decisions)
Jump Decision
Gravity Pulls Down
No Action
Keep Falling
Hits Obstacle
Restart Training
Flap (Jump)
No Action (Fall)
Collision State (Hits Pipe/Ground)
Game Over
Game Over State (Training Updates)

DQN:

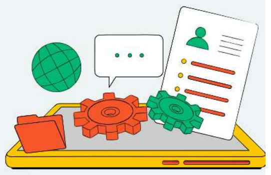


TENTATIVE PROPOSAL WORK

Deep Q-Network (DQN) is a powerful algorithm in the field of reinforcement learning. It combines the principles of deep neural networks with Q-learning, enabling agents to learn optimal policies in complex environments

Core Concepts:

- Q-Learning: DQN leverages the Q-learning algorithm, which aims to estimate the optimal action-value function (Q-function) that maps states to expected future rewards.
- Experience Replay: Experience replay helps in decorrelating the sequential experiences by storing them in a replay memory buffer. This memory buffer is randomly sampled during the network update to break the temporal dependencies and stabilize learning.



Input Layer:
The input consists of state representations, which in the case of Flappy Bird would be the pixels of the game screen. These images are fed into the network after pre-processing (e.g., resizing, converting to grayscale).

Convolutional Layers (CNN):
DQN uses Convolutional Neural Networks (CNN) to extract hierarchical features from raw image input. The CNN helps in identifying patterns and relevant objects (such as the bird and obstacles in Flappy Bird) in the environment.

The network typically consists of several convolutional layers followed by pooling layers to reduce the spatial dimension and retain important features.

Fully Connected Layers:
After the convolutional layers, the output is flattened and passed through fully connected layers (also called dense layers). These layers help the model learn a more abstract representation of the game environment based on the extracted features.

Q-Value Output Layer:
The final layer of the DQN network outputs a Q-value for each possible action that can be taken in the environment. In the case of Flappy Bird, these actions might be "flap" or "do nothing".
The Q-value represents the expected future rewards for each action taken from the given state.

Target Network:
DQN uses a target network, which is a copy of the original Q-network. This target network is updated less frequently to stabilize the training process.
The target network helps in reducing the variance in updates by providing a more stable target during training.

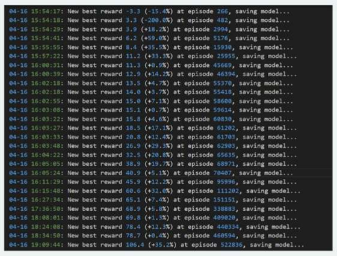
Experience Replay:
A key feature of DQN is experience replay, where the agent stores past experiences (state, action, reward, next state) in a replay buffer.
During training, random mini-batches of experiences are sampled from this buffer to update the Q-values, which helps in breaking the correlation between consecutive experiences and leads to more stable training.

Loss Function:
The loss function used in DQN is typically Mean Squared Error (MSE), which measures the difference between the predicted Q-value and the target Q-value computed from the reward and the next state's Q-values.
The target Q-value is calculated using the Bellman equation, considering the reward obtained and the maximum Q-value predicted by the target network for the next state.

Optimization:
The model is trained using gradient descent to minimize the loss function. This helps in updating the Q-values and improving the policy gradually over time.

IMPLEMENTATION & COMPARISON RESULTS

Log file:



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04-16 15:54:17: New best reward -3.3 (-15.4%) at episode 266, saving model...
04-16 15:54:18: New best reward 3.3 (-200.0%) at episode 482, saving model...
04-16 15:54:29: New best reward 3.9 (+18.2%) at episode 2994, saving model...
04-16 15:54:41: New best reward 6.2 (+59.0%) at episode 5176, saving model...
04-16 15:55:55: New best reward 8.4 (+35.5%) at episode 15930, saving model...
04-16 15:57:22: New best reward 11.2 (+33.3%) at episode 25955, saving model...
04-16 16:00:31: New best reward 11.3 (+0.9%) at episode 45669, saving model...
04-16 16:00:39: New best reward 12.9 (+14.2%) at episode 46394, saving model...
04-16 16:02:18: New best reward 13.5 (+4.7%) at episode 55370, saving model...
04-16 16:02:18: New best reward 14.0 (+3.7%) at episode 55418, saving model...
04-16 16:02:55: New best reward 15.0 (+7.1%) at episode 58600, saving model...
04-16 16:03:08: New best reward 15.1 (+0.7%) at episode 59614, saving model...
04-16 16:03:22: New best reward 15.8 (+4.6%) at episode 60830, saving model...
04-16 16:03:27: New best reward 18.5 (+17.1%) at episode 61202, saving model...
04-16 16:03:33: New best reward 20.8 (+12.4%) at episode 61703, saving model...
04-16 16:03:48: New best reward 26.9 (+29.3%) at episode 62903, saving model...
04-16 16:04:22: New best reward 32.5 (+20.8%) at episode 65635, saving model...
04-16 16:05:05: New best reward 38.9 (+19.7%) at episode 68971, saving model...
04-16 16:05:24: New best reward 40.9 (+5.1%) at episode 70407, saving model...
04-16 16:11:29: New best reward 45.9 (+12.2%) at episode 95996, saving model...
04-16 16:15:48: New best reward 60.6 (+32.0%) at episode 111202, saving model...
04-16 16:27:34: New best reward 65.1 (+7.4%) at episode 151151, saving model...
04-16 17:36:50: New best reward 68.9 (+5.8%) at episode 338883, saving model...
04-16 18:08:01: New best reward 69.8 (+1.3%) at episode 409020, saving model...
04-16 18:24:08: New best reward 78.4 (+12.3%) at episode 440334, saving model...
04-16 18:34:50: New best reward 78.7 (+0.4%) at episode 460594, saving model...
04-16 19:09:44: New best reward 106.4 (+35.2%) at episode 522836, saving model...
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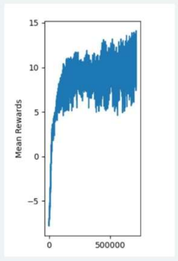
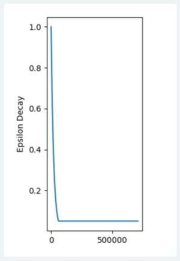
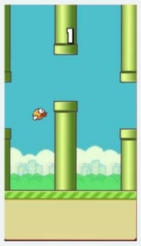
Rewards

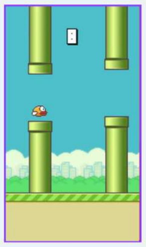


Epsilon Decay



working





CONCLUSION

This study successfully demonstrates the automation of Flappy Bird using deep learning, highlighting the potential of reinforcement learning in sequential decision-making tasks. The AI agent learns optimal gameplay strategies by processing visual inputs and making real-time decisions to maximize survival. Through techniques like experience replay and target networks, training stability and efficiency are significantly improved. The results showcase the effectiveness of deep learning in handling pixel-based environments with discrete action spaces. While the model performs well in learning game dynamics, challenges such as reward sparsity and training convergence remain. Future enhancements can include advanced optimization techniques to improve learning efficiency and adaptability. This research contributes to AI-driven game automation and can serve as a foundation for applying deep learning to more complex decision-making tasks beyond gaming.

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