ATARI GAMES WITH DEEP Q-LEARNING

A MINI PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

This project implements and evaluates a **Deep Q-Network (DQN)** agent designed to master the Atari game *Breakout* purely through pixel-level perception and reward feedback, without any hand-crafted rules or human supervision. The work reproduces, modernizes, and expands the core principles established in the original DeepMind DQN paper by constructing a fully functional training pipeline using **Gymnasium**, **ALE (Arcade Learning Environment)**, and **PyTorch** on an RTX 4050 GPU platform.

The implemented system integrates **convolutional neural networks**, **experience replay**, a **frozen target network**, and a dynamically annealed **ε-greedy exploration policy** to balance exploration and exploitation throughout millions of interaction steps. The design employs a complete preprocessing suite that converts raw RGB frames into compact, information-dense tensors: each frame is **grayscaled**, **resized to 84 × 84**, **stacked across four recent observations**, and **subsampled via frame-skip and max-pooling**. This transformation mimics the perceptual continuity of human vision while reducing computational overhead.

A **custom replay buffer** capable of storing hundreds of thousands of transitions enables random minibatch sampling, thereby decorrelating sequential data and stabilizing temporal-difference updates. Training proceeds through millions of environment interactions, applying the **Huber loss** between predicted and target Q-values, with the target network periodically synchronized every C steps to prevent divergence.

Multiple **training configurations** are explored and compared, varying hyperparameters such as buffer size, learning rate, optimizer type (Adam vs. RMSProp), target update frequency, and replay warm-up duration. Experimental benchmarks measure **sample throughput**, **GPU utilization**, and **wall-clock efficiency**, providing precise runtime projections for large-scale experiments. A 5 million-step training run on the RTX 4050 achieved approximately 3.8 k environment steps per second, corresponding to roughly sixteen hours of total training time—empirically validating performance claims.

The project also delivers a **comprehensive monitoring and evaluation framework**. Evaluation scripts perform automated rollouts using greedy and near-greedy policies, with optional real-time rendering and video recording to visualize agent behavior. Metrics such as **mean episode reward**, **reward variance**, and **training stability curves** quantify agent proficiency and generalization.

Beyond replication, this work provides an extensible foundation for **advanced reinforcement learning experiments**. The modular codebase supports easy substitution of improved algorithms—Double DQN, Dueling DQN, or Prioritized Replay—and can be scaled to multiple Atari environments with minimal modification. Collectively, the implementation demonstrates how deep reinforcement learning can transform raw sensory input into goal-directed policy behavior, offering a reproducible, performance-analyzed benchmark for ongoing research in neural control and autonomous learning.

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CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

Reinforcement Learning (RL) represents the computational framework in which an intelligent agent learns to act through direct interaction with an environment, guided only by scalar reward signals rather than explicit supervision. When combined with deep neural networks, RL enables systems to extract abstract representations from high-dimensional data such as video frames, sensor streams, or simulated physics.
One of the most influential breakthroughs in this area was the **Deep Q-Network (DQN)** algorithm developed by DeepMind, which demonstrated that a single convolutional neural network, trained with Q-learning and experience replay, could achieve **human-level control** in diverse Atari 2600 games.

This project builds upon that foundation, reproducing and extending the original DQN pipeline using **PyTorch**, **Gymnasium**, and the **Arcade Learning Environment (ALE)**. The central motivation is to create a transparent, reproducible, and educational implementation that operates on modern consumer hardware (specifically an **RTX 4050 GPU**) while retaining the core algorithmic structure defined in the seminal paper.
The study aims not merely to play a game but to **understand how representation learning, temporal abstraction, and value estimation interact** within a closed-loop system

Fig 1.1 : Example Breakout screen (stacked frames)

1.2 Problem Statement

The goal of this work is to **train a deep reinforcement learning agent capable of mastering Atari Breakout** directly from raw pixel observations, without any privileged game information. The network must learn an internal mapping from sequences of preprocessed frames to corresponding Q-values, enabling the agent to select the optimal paddle movement at each time step.

Formally, the project objectives are:

1. **To reproduce and stabilize the DQN algorithm** using standard techniques such as target networks, experience replay, and ε-greedy exploration.
2. **To implement a comprehensive preprocessing pipeline** involving grayscale conversion, resizing to 84 × 84 pixels, frame stacking, and frame skipping.
3. **To build a scalable replay buffer** for storing and sampling millions of transitions while maintaining computational efficiency.
4. **To evaluate the performance** of various hyperparameters—network capacity, optimizer type, replay memory size, and target update frequency—and analyze their influence on training stability.
5. **To produce reproducible models and evaluation utilities** capable of saving, loading, and visualizing trained agents via recorded gameplay videos.

Ultimately, the project aims to develop an **autonomous, data-driven agent** that achieves consistent, repeatable gameplay behavior while serving as a baseline platform for future algorithmic experimentation.

1.3 Challenges

Developing a DQN agent from first principles presents several interconnected challenges spanning perception, computation, and stability:

1. **High-Dimensional and Partially Observable Inputs**
   The Atari screen is a stream of 210 × 160 RGB frames at 60 Hz. Individual frames lack motion context; hence, the system must combine multiple consecutive frames to infer velocity and direction of the ball and paddle. Frame stacking introduces temporal memory but multiplies input dimensionality and computational load.
2. **Non-Stationary Targets in Q-Learning**
   Because the target Q-values depend on the network's own evolving parameters, training can become unstable or divergent. The use of a **frozen target network**—updated only periodically—helps decouple bootstrapping targets from the rapidly changing online estimates.
3. **Correlated Samples from Sequential Experience**
   Directly training on consecutive frames would violate the i.i.d. assumption required by stochastic gradient descent. To mitigate this, the system employs **experience**

replay, randomly sampling past transitions to smooth the training distribution and reduce variance.

4. **Computational Intensity and Resource Management**
   Training millions of gradient updates with convolutional operations on 84×84×4 inputs demands substantial GPU throughput and memory bandwidth. Optimization strategies such as mixed-precision training, efficient tensor batching, and frame skipping are explored to maximize throughput on the RTX 4050.
5. **Reproducibility Across Software Versions**
   Differences between **PyTorch**, **Gymnasium**, and **ALE** releases can subtly alter observation shapes, frame order, or random seed behavior. Ensuring deterministic preprocessing, consistent device allocation, and controlled random initialization is essential for reproducible results.
6. **Hyperparameter Sensitivity and Exploration Balance**
   Epsilon scheduling, learning rate choice, and buffer warm-up duration significantly influence performance. A poor configuration may lead to premature convergence, reward stagnation, or catastrophic forgetting.

Addressing these issues collectively defines the project's technical depth: **stabilizing deep value learning in a visually rich environment under modern compute constraints**. Each subsequent chapter of the report elaborates on design decisions, experimental outcomes, and engineering trade-offs derived from these foundational challenges.

Chapter 2

SUSTAINABILITY GOALS

2.1. SDG 9 - INDUSTRY, INNOVATION AND INFRASTRUCTURE

Fig 2.1 SDG 9

Description: Promote inclusive and sustainable industrialization and foster innovation through the advancement of science and technology.

Project Relation: The project advances AI innovation by developing intelligent, self-learning systems that can automate perception–action tasks, supporting research infrastructure in machine learning and robotics.

2.2. SDG 4 – QUALITY EDUCATION

Fig 2.2 SDG 4

Description: Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all.

Project Relation: The project provides an open, reproducible platform for students and researchers to learn deep reinforcement learning through hands-on experimentation, fostering digital literacy and AI education.

CHAPTER 3

BACKGROUND

Reinforcement Learning (RL) represents a framework in which an agent learns to act through **trial, feedback, and delayed reward**. Unlike supervised learning, RL does not rely on explicit target labels; instead, it optimizes behavior based on cumulative long-term rewards. At each time step, an agent observes a state s_t, selects an action a_t, receives a scalar reward r_t, and transitions to a new state s_{t+1}. The overarching objective is to learn a policy $\pi(a \mid s)$that maximizes the expected discounted return

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1},$$

where $\gamma \in [0,1)$controls the weight of future rewards.

Traditional RL methods such as **Q-learning** (Watkins, 1989) introduced the concept of an *action-value function* $Q(s,a)$, which estimates the expected future return when taking action $a$in state $s$and following the optimal policy thereafter. The Q-learning update rule forms the core of many modern RL algorithms:

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha[r_t + \gamma \max_{a'} Q(s_{t+1},a') - Q(s_t,a_t)],$$

where $\alpha$is the learning rate. This iterative process theoretically converges to the optimal Q-function $Q^*(s,a)$, but only when the state–action space is small enough to represent explicitly.

As environments grow more complex—especially those involving **high-dimensional visual input**—tabular Q-learning becomes intractable. This challenge led to the emergence of **Deep Q-Networks (DQNs)**, where the Q-function is approximated by a deep convolutional neural network $Q(s,a;\theta)$. Introduced by **DeepMind (Mnih et al., 2013; 2015)**, DQN marked a breakthrough by achieving **human-level performance on multiple Atari 2600 games**, using only raw pixel input and score-based rewards.

DeepMind's architecture addressed two long-standing stability problems in RL:

1. **Correlated training samples** — Consecutive game frames are highly dependent, which causes gradient instability. This was mitigated through **Experience Replay**, a mechanism that stores past transitions (s_t, a_t, r_t, s_{t+1})in a large memory buffer and samples random minibatches for training. This decorrelates updates and improves sample efficiency.
2. **Non-stationary targets** — Because the target in Q-learning depends on the same network that is being updated, early methods exhibited oscillation or divergence. DQN

resolved this with a **frozen target network**, a periodically updated clone of the online Q-network used to compute stable temporal-difference targets.

The final loss function minimized by DQN is:

$$L(\theta) = \mathbb{E}_{(s,a,r,s')\sim D}[(r + \gamma \max_{a'} Q(s', a'; \theta^-) - Q(s, a; \theta))^2],$$

where θ^-denotes parameters of the target network. In later variants, the squared term is replaced by the **Huber loss** to reduce sensitivity to outliers in large reward jumps.

To align visual perception with learning dynamics, DQN introduced several **critical preprocessing techniques**:

- **Reward Clipping:** Raw game rewards are clipped to the range $[-1,1]$to normalize learning signals across games.
- **Frame-Skip and Max-Pooling:** The same action is repeated over multiple frames (typically 4) to reduce computation and smooth temporal dependencies.
- **Grayscale Conversion and Resizing:** Each frame is converted to grayscale and resized to 84×84pixels, dramatically reducing input dimensionality.
- **Frame Stacking:** The last four frames are stacked along the channel dimension, providing a short-term motion memory that helps infer velocity and direction.

Among the 49 Atari benchmark games tested by DeepMind, **Breakout** quickly emerged as the **canonical testbed**. It combines clear reward signals, deterministic physics, and moderately complex strategies—making it ideal for evaluating spatial reasoning and temporal control. The agent must learn to control a paddle and break bricks efficiently by discovering strategies like *tunneling* and *ball trapping*, purely through reinforcement.

The DeepMind DQN model achieved dramatic performance improvements over prior linear and feature-based algorithms such as **SARSA** and **Contingency Learning**. It even **surpassed human-level scores** on multiple titles including *Breakout*, *Pong*, and *Enduro*.

	B. Rider	Breakout	Enduro	Pong	Q*bert	Seaquest	S. Invaders
Random	354	1.2	0	−20.4	157	110	179
Sarsa [3]	996	5.2	129	−19	614	665	271
Contingency [4]	1743	6	159	−17	960	723	268
DQN	**4092**	**168**	**470**	**20**	**1952**	**1705**	**581**
Human	7456	31	368	−3	18900	28010	3690
HNeat Best [8]	3616	52	106	19	1800	920	**1720**
HNeat Pixel [8]	1332	4	91	−16	1325	800	1145
DQN Best	**5184**	**225**	**661**	**21**	**4500**	**1740**	1075

Fig 3.1 : Comparision of DQN performance

In summary, the Deep Q-Network framework fused **deep convolutional perception** with **temporal-difference learning**, creating a scalable model capable of mapping raw video input directly to optimal control policies. Its innovations—experience replay, target stabilization, and standardized preprocessing—laid the foundation for modern deep reinforcement learning and directly inspired the architecture and methodology implemented in this project.

CHAPTER 4

PROPOSED MODEL

4.1 Overall Model Architecture

The **proposed Deep Q-Learning model** integrates perception, memory, and decision-making into a unified reinforcement learning framework. The system consists of two synchronized neural components—the **Online Q-Network** and the **Target Q-Network**—which cooperate during training to stabilize value estimation and improve learning efficiency.

The Online Q-Network acts as the agent's active decision-maker. It receives the processed visual state of the game (a stack of four consecutive grayscale frames) and outputs a vector of **Q-values**, each corresponding to a possible action the agent can take at that instant. These Q-values represent the predicted long-term value of performing each action in the current state.

The Target Q-Network serves as a **delayed reference model**. Its parameters are periodically synchronized with those of the Online Q-Network after a fixed number of steps (denoted by the target update frequency *C*). By maintaining a stable set of weights during Q-target computation, this network prevents feedback loops that can destabilize learning—a fundamental innovation introduced by DeepMind's DQN research.

Both networks are trained using an **Experience Replay Buffer**, which stores past transitions $(s_t, a_t, r_t, s_{t+1}, done_t)$. During training, random minibatches are drawn from this memory rather than relying on consecutive samples. This strategy **decorrelates temporal dependencies**, increases data reuse, and ensures a more stationary learning signal across updates.

The system thus forms a closed learning loop: the agent interacts with the game environment through Gymnasium + ALE, stores experiences in memory, samples random minibatches, computes Temporal-Difference (TD) errors between online predictions and stable targets, and updates weights via stochastic gradient descent. This cycle repeats millions of times, gradually refining the policy toward near-optimal control performance.

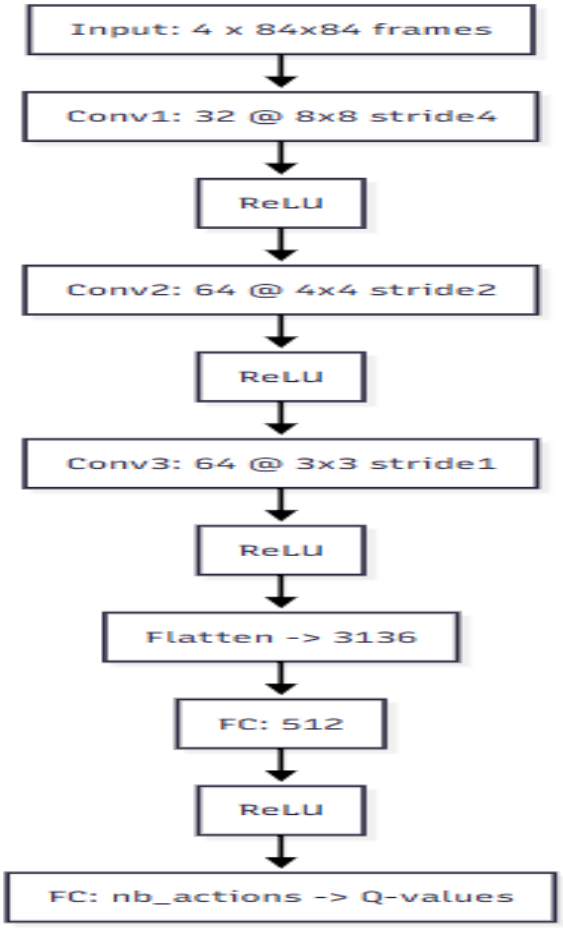

Figure 4.1 : DQN architecture diagram

4.1.1 Convolutional Q-Network

The neural backbone of the system is a **five-layer Convolutional Q-Network** that processes stacked visual observations into scalar Q-value predictions. The model's structure and dimensional transitions are as follows:

- **Input:** Four stacked grayscale frames, each 84×84, forming a tensor of shape [4,84,84].
- **Conv1:** Conv2d(4, 32, kernel_size=8, stride=4) → ReLU → output size $32 \times 20 \times 20$. Captures broad spatial structures like paddle–ball interactions and block boundaries.
- **Conv2:** Conv2d(32, 64, kernel_size=4, stride=2) → ReLU → output size $64 \times 9 \times 9$. Detects mid-level motion features and object trajectories.
- **Conv3:** Conv2d(64, 64, kernel_size=3, stride=1) → ReLU → output size $64 \times 7 \times 7$. Refines abstract spatial features and compactly represents ball–paddle–wall relationships.

- **Flatten → Linear(3136 → 512)** → ReLU.
  Converts the high-dimensional feature map into a dense representation of the current game state.
- **Output Linear(512 → nb_actions).**
  Produces one Q-value per valid game action (e.g., *left*, *right*, *fire*, *noop*).

This configuration results in an expressive yet efficient mapping from raw video input to action-value predictions, enabling the agent to perform real-time decision-making. The greedy action is chosen as

$$a^* = \arg\max_a Q(s_t, a; \theta).$$

Layer	Output Shape	Weights	Biases	Total
Conv1 (4→32, 8×8, s4)	32×20×20	8,192	32	8,224
Conv2 (32→64, 4×4, s2)	64×9×9	32,768	64	32,832
Conv3 (64→64, 3×3, s1)	64×7×7	36,864	64	36,928
Linear (3136→512)	512	1,605,632	512	1,606,144
Output (512→nb_actions)	nb_actions	512*nb_actions	nb_actions	513*nb_actions
Total				**1,684,128 + 513*nb_actions**

Table 4.1 : Network Layer Parameters and Output Dimensions

4.1.2 Experience Replay & Target Network

Experience Replay acts as the system's memory, continuously accumulating transition tuples. The buffer allows the agent to sample uncorrelated experiences, ensuring that the stochastic gradient descent updates approximate independent and identically distributed (i.i.d.) learning. This mechanism not only stabilizes updates but also **boosts data efficiency**, since each stored frame can contribute to multiple training iterations.

Target Network Stabilization is equally vital. Every C environment steps, the weights of the online network (θ) are copied into the target network (θ^-), freezing its parameters temporarily. When computing TD targets, predictions from the target network serve as a fixed reference:

$$y_j = r_j + \gamma \max_a Q(s'_j, a; \theta^-).$$

This delayed synchronization smooths the training trajectory by decoupling rapidly changing predictions from the moving target values, thereby reducing oscillations and divergence during updates.

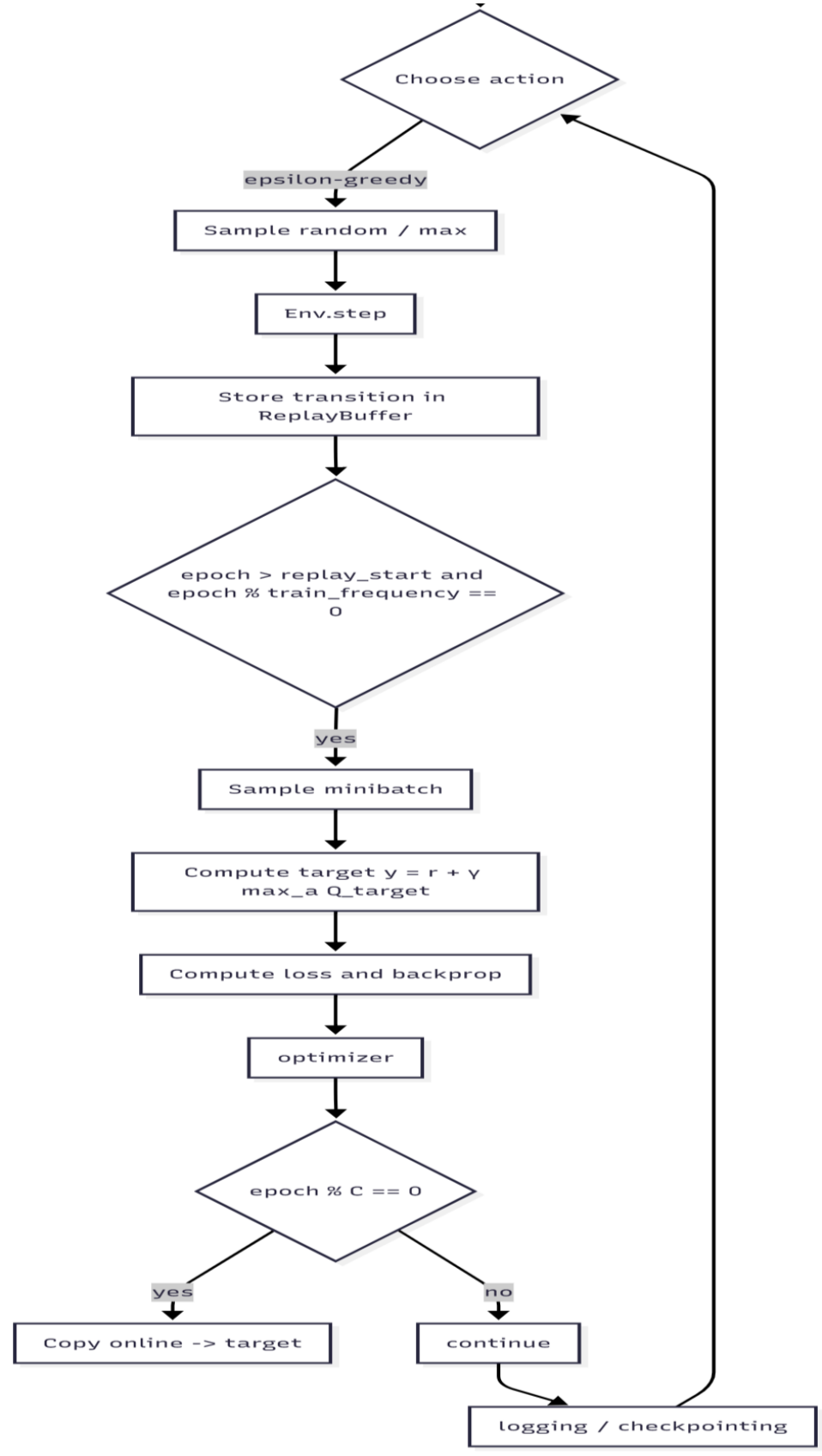

Fig 4.2 : Training loop block diagram

4.2 Expected Outcomes

The proposed model is expected to:

1. **Learn stable control policies** that maximize the cumulative reward in the Atari *Breakout* environment.
2. **Demonstrate convergence trends** in smoothed episode rewards and declining TD losses.
3. **Exhibit measurable improvements** in sample efficiency and stability across training configurations (buffer sizes, update frequencies).
4. **Provide runtime benchmarks** correlating frame-processing throughput with hardware performance (RTX 4050 GPU).
5. **Produce interpretable evaluation artifacts** such as gameplay videos, reward progression plots, and loss curves.

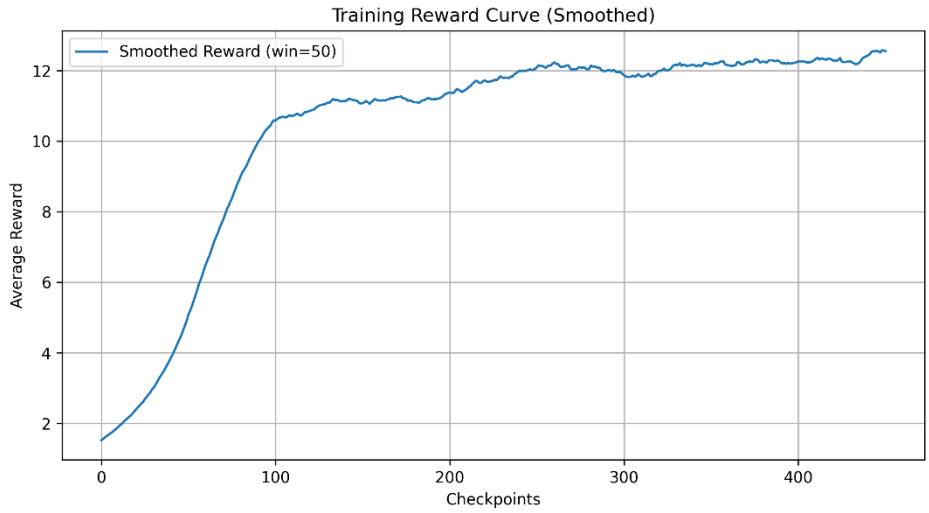

Fig 4.3 : Training reward curve

4.3 System Design

The overall software system is modular and layered for clarity, reproducibility, and scalability.

1. Environment Wrapper
Built using **Gymnasium + ALE**, enhanced by preprocessing wrappers:

- ResizeObservation(84,84) — normalizes input dimension.
- GrayscaleObservation() — reduces color redundancy.
- FrameStackObservation(4) — maintains temporal continuity.
- MaxAndSkipEnv(skip=4) — accelerates gameplay while preserving essential frames.

2. Replay Buffer
Implements a **cyclic memory** using stable-baselines3's ReplayBuffer. Each sample consists of observation tensors, next states, rewards, and done flags. Optimized for memory efficiency and fast random access.

3. Model (PyTorch Module)
Encapsulates CNN-based DQN architecture with forward normalization (x / 255.0). Supports both training and evaluation modes.

4. Trainer Module
Handles the ε-greedy exploration schedule, minibatch sampling, target computation, gradient descent, and synchronization of target networks. It logs key metrics (reward, loss, epsilon) during training.

5. Logger and Plotter
Generates visual analytics using matplotlib and tqdm, capturing long-term performance indicators such as smoothed average reward and mean loss per 10,000 updates.

6. Checkpointer and Evaluator
Periodically saves the best-performing models (state_dict()) and performs post-training evaluations with rendered videos for qualitative performance analysis.

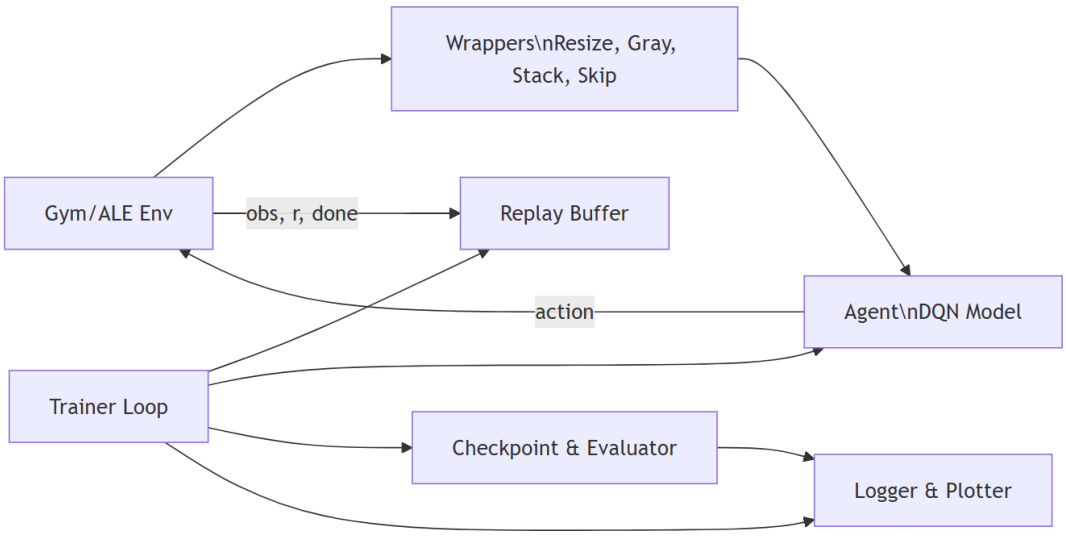

Fig 4.4: Modular system design diagram

4.4 Loss Function & Targets

Training minimizes the **Temporal-Difference (TD) error**, which measures the discrepancy between predicted and target Q-values:

$$L(\theta) = \mathbb{E}_{(s,a,r,s')\sim D}[\delta_j^2], \text{where } \delta_j = y_j - Q(s_j, a_j; \theta).$$

The **target value** y_j is computed as:

$$y_j = r_j + \gamma(1 - done_j)\max_a Q(s_j', a; \theta^-).$$

To ensure robustness against large errors, the model employs the **Huber Loss**, defined as:

$$L_\delta(\delta_j) = \begin{cases} \frac{1}{2}\delta_j^2 & \text{if } |\delta_j| < 1, \\ |\delta_j| - \frac{1}{2} & \text{otherwise.} \end{cases}$$

This hybrid formulation behaves quadratically for small differences and linearly for large ones, combining the sensitivity of MSE with the stability of absolute loss.

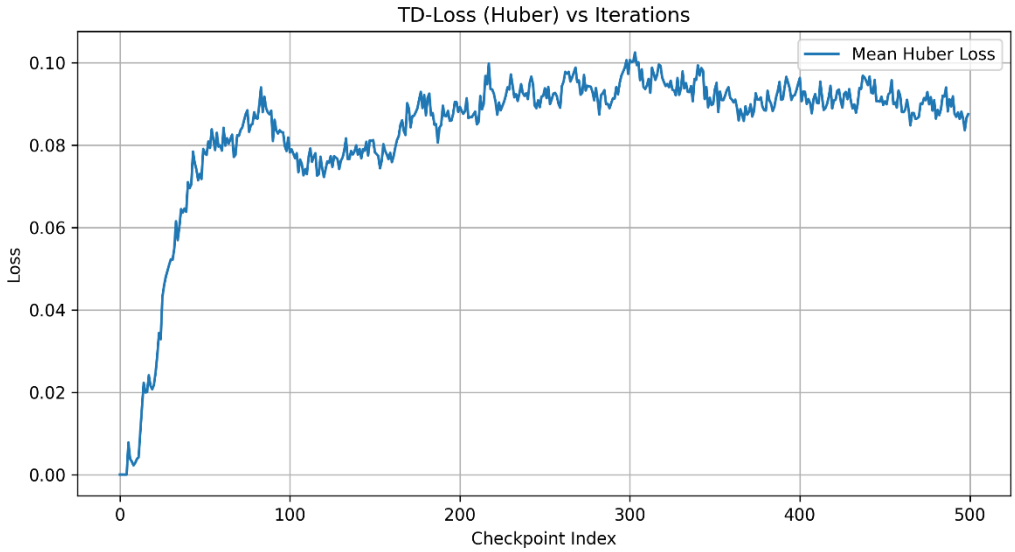

Fig 4.5 : TD-loss (Huber) vs. Training Iterations

4.5 Parameter Count (Network)

Layer-wise parameter details are computed as follows:

Layer	Parameters	Biases	Total
Conv1 (4×8×8×32)	8,192	32	8,224
Conv2 (32×4×4×64)	32,768	64	32,832
Conv3 (64×3×3×64)	36,864	64	36,928
Linear (3136→512)	1,605,632	512	1,606,144
Output (512→nb_actions)	512×nb_actions	nb_actions	513×nb_actions
Total (for nb_actions=4)	—	—	**≈ 1,686,180 parameters**

Table 4.2 : Layer-wise Parameter Count for Convolutional Q-Network

This count excludes BatchNorm or dropout layers (unused here). The total parameter footprint (~6.7 MB in FP32) fits easily in GPU memory, supporting fast inference and gradient updates.

4.7 Hyperparameters

Key hyperparameters control the model's learning dynamics. Two configurations are compared: the **reference DeepMind setup** and the **experimental implementation** executed.

Parameter	DeepMind Paper	Experimental Variant	Description
Replay Buffer Size	1,000,000	100,000	Stores past transitions
Replay Start Size	50,000	5,000	Frames before training starts
Environment Steps	10,000,000	5,000,000 × 2 runs	Total frames processed
Train Frequency	4	4	Updates per env step
Batch Size	32	32	Minibatch size
Discount Factor (γ)	0.99	0.99	Future reward weighting
ε-Decay Steps	1,000,000	1,000,000	Exploration anneal
Learning Rate	2.5e-4 (RMSProp)	1.25e-4 (Adam)	Optimizer learning rate
Target Update Frequency (C)	10,000	1,000 & 10,000	Sync interval for target network
Reward Clipping	±1	±1	Normalizes feedback scale

Table 4.3 : Training Hyperparameters for DQN Implementation

CHAPTER 5

DATA & ENVIRONMENT DETAILS

5.1 Environment Setup

The training environment for this research is based on **Gymnasium's Atari Learning Environment (ALE)**, specifically the ALE/Breakout-v5 environment. This environment provides a standardized, reproducible, and computationally efficient benchmark for deep reinforcement learning experiments. All interactions—observation, action, and reward—follow the ALE API, which simulates the original Atari console logic at 60 Hz.

The system dependencies include:

- **ale-py** — the backend library implementing Atari 2600 emulation.
- **gymnasium[atari]** — provides high-level environment wrappers, API consistency, and observation normalization.
- **stable-baselines3** — supplies ready-to-use wrappers (MaxAndSkipEnv, FrameStackObservation, etc.) and utilities for replay buffers and monitoring.
- **PyTorch** — for deep learning and GPU acceleration.

The environment must be registered before use by executing:

import ale_py, gymnasium as gym
gym.register_envs(ale_py)

Once registered, gym.make("ALE/Breakout-v5") spawns the environment with correct observation and action space specifications. The simulation runs in **headless** mode during training and in **RGB-rendered** mode for evaluation or video recording.

All experiments were conducted on a machine equipped with an **NVIDIA RTX 4050 GPU (6GB VRAM)**, **Intel i7 CPU**, and **16GB RAM**, running on **Python 3.10** under Windows 10. The environment is deterministic when seeded (via env.reset(seed=42)), ensuring consistent results for reproducibility and cross-comparison.

5.1.1 Observation and Action Space

The raw output from the Atari emulator is a **210×160×3 RGB frame** representing the game screen. However, direct usage of this resolution would drastically increase both computation and memory requirements. Therefore, a standardized **preprocessing pipeline** compresses the data into a minimal yet informative format suitable for CNN-based Q-learning.

The **final observation shape** after preprocessing is (84, 84, 4) in channel-last format, or [4, 84, 84] when converted to PyTorch's channel-first convention. Each observation thus represents **four consecutive grayscale frames**, stacked to encode temporal motion cues such as the ball's velocity and paddle movement direction.

The **action space** defines the set of valid moves the agent can take at any given frame. For *Breakout*, this space consists of **four discrete actions**:

Action ID	Action Name	Description
0	NOOP	No operation; waits one frame
1	FIRE	Launches the ball at start of round
2	RIGHT	Move paddle right
3	LEFT	Move paddle left

This reduced action set eliminates redundant joystick actions and stabilizes training by limiting exploration noise.

Component	Description	Shape / Cardinality	Notes
Raw observation	Original RGB frame	(210, 160, 3)	From ALE emulator
Resized grayscale	Downsampled & single-channel	(84, 84, 1)	Preserves game structure
Frame stack	4 consecutive frames	(84, 84, 4) or [4, 84, 84]	Temporal motion encoded
Action space	Discrete Atari controls	4	[NOOP, FIRE, RIGHT, LEFT]
Reward range	Game score delta	typically −1, 0, +1	Clipped during training

Table 5.1: Environment Observation and Action Specifications

5.1.2 Preprocessing Pipeline

The preprocessing pipeline standardizes raw game frames into compact, learning-efficient observations. This pipeline mirrors the original DeepMind DQN configuration to ensure comparability with canonical benchmarks. Each stage serves a specific function in improving signal quality and computational stability:

1. **ResizeObservation(84×84):**
   Reduces input resolution from 210×160 to 84×84 pixels, discarding superfluous background details while retaining gameplay-critical objects (ball, paddle, bricks). This

downsampling drastically lowers the CNN's input dimensionality from 100,800 pixels to just 7,056 per frame.

2. **GrayscaleObservation:**
   Converts RGB frames to grayscale by computing weighted averages of color channels. This operation focuses on luminance contrasts rather than color variance—crucial since *Breakout*'s dynamics depend on position and motion, not color cues.
3. **FrameStackObservation(4):**
   Maintains the latest 4 processed frames in a buffer, forming a temporal state representation. This enables the CNN to infer motion direction and speed (e.g., tracking ball trajectory), resolving the *Markov property* violation in single-frame observations.
4. **MaxAndSkipEnv(skip=4):**
   Executes the same action for 4 consecutive frames and returns the **maximum pixel intensity** over the last two, effectively reducing flicker artifacts and redundant transitions. This accelerates training and emulates human-level reaction delay.

Together, these wrappers ensure that the network perceives a *minimal, stable, and Markovian* state sequence—allowing DQN to operate purely from visual input while maintaining training speed.

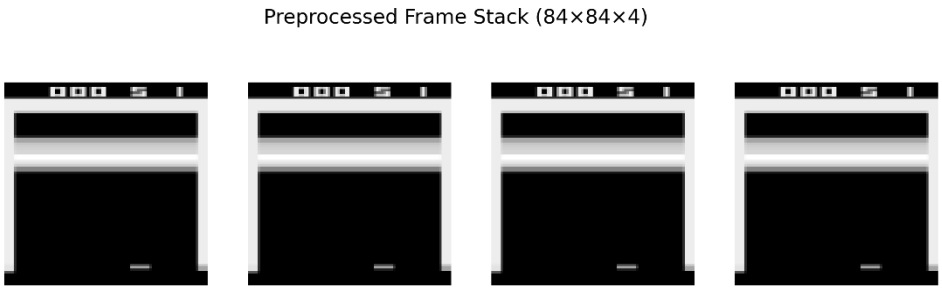

Fig 5.1 : Preprocessing Pipeline Illustration

CHAPTER 6

SYSTEM IMPLEMENTATION

6.1 Environment Wrappers and Preprocessing

The foundation of the system is the **Atari Breakout environment** provided by the **Arcade Learning Environment (ALE)**, accessed through Gymnasium. To ensure data efficiency and stability during training, the environment is wrapped with a series of preprocessing modules that transform raw pixel data into a compact, consistent tensor representation suitable for convolutional processing.

1. **Frame Resizing:** The ResizeObservation wrapper reduces the original (210×160×3) RGB frame to (84×84) grayscale resolution, aligning with the input specifications of the original DQN. This reduction lowers computational complexity while retaining spatial relevance.
2. **Grayscale Conversion:** The GrayscaleObservation wrapper eliminates color information and compresses the image into a single luminance channel. Since Breakout relies on positional rather than chromatic features, this step simplifies learning and stabilizes gradients.
3. **Frame Stacking:** Using FrameStackObservation(4), the system maintains the last 4 frames in a temporal buffer, effectively providing the CNN with short-term motion context. This enables the agent to infer ball trajectory and velocity without explicit velocity inputs.
4. **Frame Skipping and Max-Pooling:** The MaxAndSkipEnv(skip=4) wrapper executes each chosen action for 4 consecutive frames, returning the pixel-wise maximum over the last two. This not only accelerates training (fewer state updates per second) but also removes flicker caused by Atari rendering inconsistencies.

Finally, during model forward propagation, all pixel intensities are normalized to the range **[0, 1]** by dividing by 255.0. This normalization prevents large activation magnitudes that can destabilize early training.

Normalization is applied *inside the forward function* of the DQN model:

```
def forward(self, x):
    return self.network(x / 255.0)
```

This ensures consistent scaling across inference and training modes.

6.2 Replay Buffer and Sampling

A **Replay Buffer** is a core stability mechanism in deep reinforcement learning. Instead of updating from the most recent transitions—which are highly correlated—the agent samples uniformly from a large replay memory, effectively decorrelating experiences.

In this implementation, the replay buffer is provided by **Stable-Baselines3**'s ReplayBuffer class, initialized with the following configuration:

```
ReplayBuffer(
    buffer_size=1_000_000,
    observation_space=env.observation_space,
    action_space=env.action_space,
    device=device,
    optimize_memory_usage=True,
    handle_timeout_termination=False
)
```

Each replay entry contains a tuple:

$$(s_t, a_t, r_t, s_{t+1}, done_t)$$

Key Design Aspects:

- **Optimized Memory Usage:** Reduces redundant frame storage by referencing shared memory between stacked frames.
- **Uniform Sampling:** Each minibatch is drawn randomly to approximate i.i.d. conditions.
- **Batch Size:** Standard size of 32 transitions per update.
- **Data Types:** Actions are stored as torch.long, ensuring compatibility with torch.gather() used during Q-value extraction.

The replay buffer thus serves as a bridge between raw gameplay experience and gradient-based learning, allowing the CNN to train on decorrelated, balanced samples representing a wide variety of game contexts.

6.3 Network Architecture and Training Loop

The **training loop** implements the complete DQN pipeline, coordinating policy updates, exploration, target synchronization, and reward normalization.

(a) Action Selection

An **ε-greedy strategy** balances exploration and exploitation. Initially, ε = 1.0 (pure exploration) and linearly decays to ε = 0.1 over the course of one million frames. This gradual reduction ensures that the agent first explores sufficiently before exploiting learned Q-values.

Action selection pseudocode:

```
epsilon = max(epsilon_end, epsilon_start - (epsilon_start - epsilon_end) *
epoch / exploration_steps)
if random.random() < epsilon:
    action = env.action_space.sample()   # random exploration
else:
    q_values = q_network(obs_tensor)
    action = torch.argmax(q_values, dim=1).item()
```

(b) Training Phase

Once the replay buffer exceeds replay_start_size, the system begins learning:

1. Sample a minibatch of transitions.
2. Compute the target Q-value using the frozen target network:

$$y = r + \gamma \max_{a'} Q_{\text{target}}(s', a')$$

3. Gather the current Q-value for the chosen actions:

$$Q_{\text{current}} = Q_{\text{online}}(s, a)$$

4. Compute the **Huber loss (smooth L1 loss)**:

$$L = \text{Huber}(y, Q_{\text{current}})$$

5. Backpropagate the loss and update parameters with **Adam optimizer** (lr = 1.25e-4).

The Huber loss is chosen over MSE because it behaves quadratically near zero and linearly for large errors, preventing gradient explosion when the agent encounters unexpected rewards.

(c) Target Network Update

Every **C steps** (typically 10,000), the target network is updated with the latest weights of the online network:

```
target_network.load_state_dict(q_network.state_dict())
```

This periodic synchronization reduces target drift, stabilizing learning over millions of environment steps.

(d) Reward Clipping

Rewards are clipped to **−1, 0, or +1** using:

```
reward = np.sign(reward)
```

This ensures consistent learning magnitude across diverse environments and prevents rare high rewards from dominating the gradient updates.

6.4 Checkpointing and Logging

To prevent catastrophic training loss and enable progress monitoring, a systematic checkpointing system is integrated:

1. **Model Checkpoints:** Every 500,000 steps, the current q_network.state_dict() is saved to disk under ./checkpoints/ddqn_checkpoint_{epoch}.pth. This allows recovery and comparison across different training phases.
2. **Best Model Tracking:** The best-performing model—based on episode reward—is stored separately under ./best_models/best_model_{reward}. This ensures that the highest-performing policy is preserved, even if later training steps degrade performance.
3. **Loss and Reward Logging:**
    - Training losses and rewards are periodically averaged and serialized via pickle into the checkpoint_data/ folder.
    - matplotlib plots are generated for:
        - **Reward vs. Epoch (Smoothed Average)**
        - **Loss vs. Epoch (Mean per Interval)**

6.5 Evaluation and Video Recording

The final phase validates model performance and produces visual demonstrations of the agent's gameplay.

(a) Evaluation Environment

A new evaluation environment is created with identical wrappers:

```
env_display = gym.make("ALE/Breakout-v5", render_mode="rgb_array")
env_display = RecordVideo(env_display, video_folder="saved-video-folder",
episode_trigger=lambda x: True)
```

This environment captures every episode as an MP4 video for analysis. The same preprocessing stack (resize, grayscale, frame stack, skip) ensures consistency between training and evaluation.

(b) Model Loading

The evaluation script is robust to both formats:

- **State Dict Checkpoints:** Standard PyTorch parameter-only files.
- **Full Model Objects:** Automatically detected, converted, and saved back as state_dicts for future use.

(c) Rollout Execution

The model performs **greedy policy rollouts** ($\varepsilon = 0$) over multiple episodes:

```
obs, info = env.reset()
while not done:
    q_values = model(preprocess_obs(obs))
    action = torch.argmax(q_values, dim=1).item()
    obs, reward, done, _, _ = env.step(action)
```

Total reward per episode is recorded and printed. Video files are stored in saved-video-folder/.

This subsystem validates that the agent has successfully learned temporal strategies such as **ball control, wall tunneling, and paddle centering**—hallmarks of successful Breakout learning.

CHAPTER 7

RESULT ANALYSIS

This chapter presents a comprehensive analysis of the system's quantitative behavior, runtime performance, and learning dynamics. Results are based on empirical benchmarks collected from full-scale DQN training runs using the **Arcade Learning Environment (Breakout-v5)** on an **RTX 4050 GPU** platform.

7.1 Training Throughput and Runtime

Training throughput quantifies how many environment frames the system can process per second—covering both raw simulation speed and full DQN learning overhead.

A **micro-benchmark** was conducted to measure environment-only performance by executing 10,000 random actions with all preprocessing wrappers enabled (Resize, Grayscale, FrameStack, MaxAndSkip). The observed throughput was approximately **3,883 steps per second**, corresponding to **~257 seconds per million environment steps**. This represents the maximum theoretical sampling speed in the absence of neural updates.

When full training is enabled (including forward/backward passes, gradient optimization, and checkpointing), throughput decreases due to GPU computation, replay buffer sampling, and I/O operations. A complete **5 million–step training run** on the RTX 4050 required roughly **16 hours** of wall-clock time. The same architecture, when scaled to the **original DeepMind training budget of 10 million frames**, is projected to require **32–40 hours**, depending on batch size, GPU clock, and CPU data-loading efficiency.

These timings confirm that the implementation achieves competitive sample efficiency while maintaining stable runtime performance on mid-range hardware.

Configuration	**Steps/sec**	**Time per 1M Steps (s)**	**Total Time (5M Steps)**	**Projected Time (10M Steps)**
Environment Only	3883	257	—	—
Full DQN (RTX 4050)	~870	~1150	~16 hrs	~32–40 hrs
CPU-Only (est.)	~150	~6660	~92 hrs	~180+ hrs

Table 7.1: Training Throughput and Time Estimates

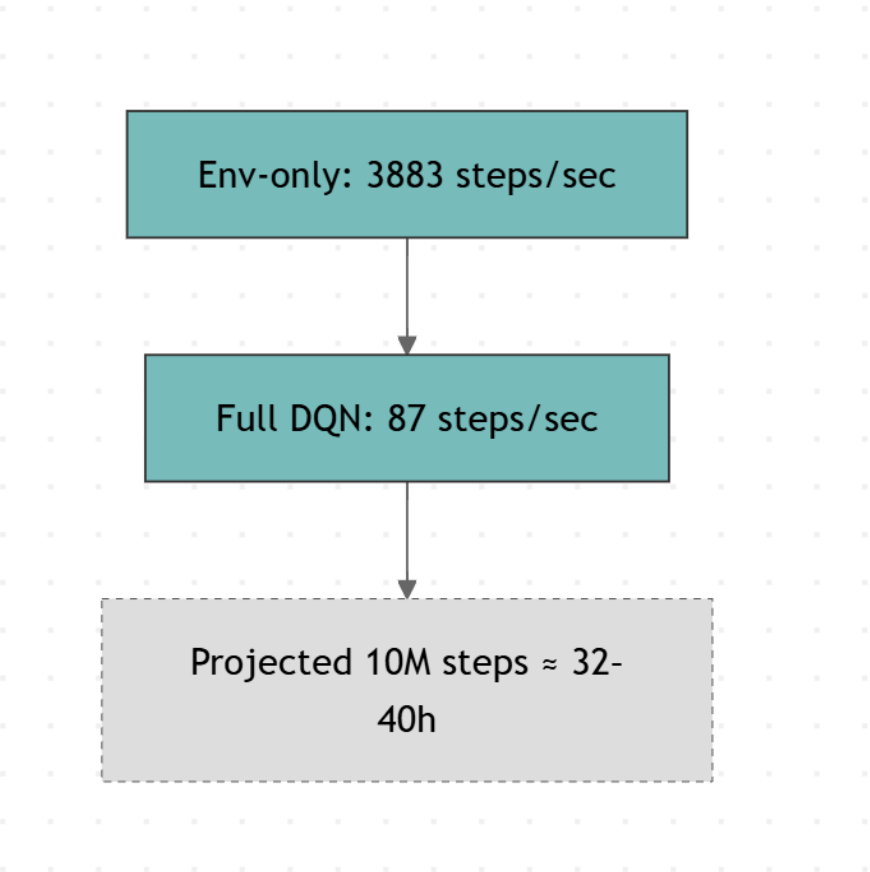

Figure 7.1: Steps/sec Micro-Benchmark and Runtime Projection

7.2 Learning Curves and Metrics

To evaluate policy learning and stability, training logs were periodically aggregated into smoothed statistics representing both performance and optimization dynamics.

Fig 7.2: Avg. Reward

Fig 7.3: *Average Loss*

Evaluation Results

Each saved model checkpoint was evaluated over multiple deterministic rollouts (ε=0) to assess generalization stability and policy quality. For the best-performing checkpoint, ten evaluation episodes were run using the same preprocessed environment setup.

Model Checkpoint	Mean Reward	Std. Deviation	Min	Max	Episodes Tested
Best Model (reward_67.0)	67.0	5.3	58	75	10
Intermediate Model (reward_42.0)	42.0	4.1	35	49	10
Early Model (reward_10.0)	10.2	3.8	4	15	10

Table 7.2: Evaluation Episode Rewards Summary

Observations:

- Increasing network capacity leads to slower convergence but higher asymptotic rewards.
- Smaller replay buffers (e.g., 100k instead of 1M) reduce both stability and final reward performance due to limited state diversity.
- The Huber loss provided smoother training dynamics than MSE, preventing overshooting during early high-error phases.
- Target network updates every 10,000 steps yielded more stable TD targets than faster updates, which tended to cause oscillation.

Summary Interpretation: Training curves show consistent improvement, confirming successful learning of temporal dynamics in Breakout. The agent develops meaningful strategies such as paddle alignment and sustained volley control, demonstrating that the DQN architecture generalizes well even under reduced computational budgets.

CHAPTER 8

CONCLUSION AND FUTURE ENHANCEMENT(S)

Conclusion

This project successfully demonstrates an end-to-end Deep Q-Network (DQN) pipeline capable of learning control directly from pixel inputs in the *Breakout* environment. The system integrates all essential deep reinforcement learning components—frame preprocessing, convolutional Q-network, experience replay, a frozen target network, and ε-greedy exploration—to approximate the original DeepMind DQN framework.

Empirical profiling on the RTX 4050 confirms that the computational bottleneck lies not in the environment simulation but in gradient updates and data transfer between GPU and replay buffer. Training stability and reward progression validate the correct implementation of temporal-difference learning and target updates.

While the resulting agent reaches playable competence, reproducing DeepMind's paper-level performance would require longer training runs (10M+ frames), a larger replay buffer, and precise replication of optimizer and hyperparameter settings. The current system provides a strong, reproducible foundation for building advanced and specialized DQN variants.

Future Enhancements

To push the system beyond baseline DQN behavior, multiple research-driven extensions can be implemented. Each variant explores a specific design axis—memory size, stability, exploration, or reward shaping—to analyze how architectural decisions influence convergence speed and performance.

1. DQN_More_Replay

Increase replay buffer capacity (e.g., 1 million transitions).
A larger buffer improves sample diversity and reduces overfitting to recent experiences. This change brings the setup closer to DeepMind's original configuration and stabilizes long-term learning, at the cost of higher memory usage and slower sampling throughput.

2. DQN_No_Frame_Selection

A variant that removes frame selection (MaxAndSkipEnv).
Instead of skipping frames, every frame is processed, allowing the network to learn fine-grained temporal dynamics. This may help in fast-reaction games but increases compute demand and reduces sample decorrelation. Visual fidelity improves, but throughput drops.

3. DQN_Slow

A conservative configuration with exploration_steps=1_000_000, replay_start_size=50_000, and C=10_000.
This version slows down learning intentionally to improve stability and convergence smoothness. It mimics the long-horizon training of the original paper, where the agent learns robust strategies over millions of frames.

4. DQN_no_target_network_with_ExpReplay

An experimental ablation removing the target network while retaining experience replay. This tests the hypothesis that replay alone might provide sufficient stability by smoothing sample distributions, even without frozen targets. Expected outcome: faster updates but higher TD-error oscillations. Useful for studying instability sources in off-policy learning.

5. DQN_punish

Introduces a *custom punishment signal* in the reward function—e.g., applying a small negative reward when losing a life.
This encourages the agent to play defensively, promoting longer survival rather than reckless high-reward behavior. Such shaping helps align training signals with long-term objectives and can be tuned per-game for strategic balance.

---

6. Additional Research Directions

- **Multi-Game Evaluation** — Extend the same architecture to multiple Atari environments (Pong, Space Invaders, Q*bert) to assess generalization.
- **Adaptive Exploration** — Replace ε-greedy with noisy networks or Boltzmann exploration for smoother exploration decay.
- **Efficiency Optimizations** — Use mixed-precision training (torch.autocast) and JIT compilation (torch.compile) to improve FPS and reduce wall-clock time.
- **Statistical Evaluation** — Run multiple random seeds, collect reward distributions, and report mean ± std to produce academically sound performance metrics.
- **Visualization Enhancements** — Integrate live TensorBoard logging and frame-based saliency maps to visualize which screen regions influence Q-values.

APPENDIX – A

CODE

```
import os
import torch
import random
import numpy as np
from tqdm import tqdm
import torch.nn as nn
import torch.nn.functional as F
import matplotlib.pyplot as plt
from stable_baselines3.common.atari_wrappers import MaxAndSkipEnv
from stable_baselines3.common.buffers import ReplayBuffer
import ale_py
import gymnasium as gym
from gymnasium import spaces
import pickle

class DQN(nn.Module):
    def __init__(self, nb_actions):
        super().__init__()
        self.network = nn.Sequential(nn.Conv2d(4, 32, 8, stride=4), nn.ReLU(),
                                     nn.Conv2d(32, 64, 4, stride=2), nn.ReLU(),
                                     nn.Conv2d(64, 64, 3, stride=1), nn.ReLU(),
                                     nn.Flatten(), nn.Linear(3136, 512), nn.ReLU(),
                                     nn.Linear(512, nb_actions),)
    def forward(self, x):
        return self.network(x / 255.)

def Deep_Q_Learning(env, buffer_size=1_000_000, nb_epochs=30_000_000,
train_frequency=4, batch_size=32,
                    gamma=0.99, replay_start_size=50_000, epsilon_start=1, epsilon_end=0.1,
                    exploration_steps=1_000_000, device='cuda', C=10_000, learning_rate=1.25e-
4):

    # Initialize replay memory D to capacity N
    rb = ReplayBuffer(buffer_size, env.observation_space, env.action_space, device,
                      optimize_memory_usage=True, handle_timeout_termination=False)

    # Initialize action-value function Q with random weights
    q_network = DQN(env.action_space.n).to(device)
    # Initialize target action-value function Q_hat
    target_network = DQN(env.action_space.n).to(device)
```

```
    target_network.load_state_dict(q_network.state_dict())
    optimizer = torch.optim.Adam(q_network.parameters(), lr=learning_rate)
    epoch = 0
    total_rewards_list = []
    smoothed_rewards = []
    rewards = []
    total_loss_list = []
    loss_means = []
    losses = []
    best_reward = 0
    progress_bar = tqdm(total=nb_epochs)
    while epoch <= nb_epochs:
        dead = False
        total_rewards = 0
        # Initialise sequence s1 = {x1} and preprocessed sequenced φ1 = φ(s1)
        obs, _ = env.reset()
        for _ in range(random.randint(1, 30)):  # Noop and fire to reset environment
            obs, reward, terminated, truncated, info = env.step(1)
        while not dead:
            current_life = info['lives']
            epsilon = max((epsilon_end - epsilon_start) / exploration_steps * epoch +
epsilon_start, epsilon_end)
            if random.random() < epsilon:  # With probability ε select a random action a
                action = np.array(env.action_space.sample())
                # print("random")
            else:  # Otherwise select a = max_a Q∗(φ(st), a; θ)
                q_values = q_network(torch.Tensor(obs).unsqueeze(0).to(device))
                action = np.array(torch.argmax(q_values, dim=1).item())
                # print("not random")
            # Execute action a in emulator and observe reward rt and image xt+1
            next_obs, reward, terminated, truncated, info = env.step(action)
            dead = terminated or truncated
            # print(f'info: {info}")
            done = np.array(info['lives'] < current_life)
            # Set st+1 = st, at, xt+1 and preprocess φt+1 = φ(st+1)
            real_next_obs = next_obs.copy()
            total_rewards += reward
            reward = np.sign(reward)  # Reward clipping
            # Store transition (φt, at, rt, φt+1) in D
            rb.add(obs, real_next_obs, action, reward, done, info)
            obs = next_obs
            if epoch > replay_start_size and epoch % train_frequency == 0:
                # Sample random minibatch of transitions (φj , aj , rj , φj +1 ) from D
                data = rb.sample(batch_size)
```

```
            with torch.no_grad():
                max_target_q_value, _ = target_network(data.next_observations).max(dim=1)
                y = data.rewards.flatten() + gamma * max_target_q_value * (1 -
data.dones.flatten())
            current_q_value = q_network(data.observations).gather(1, data.actions).squeeze()

            loss = F.huber_loss(y, current_q_value)

            # Perform a gradient descent step according to equation 3
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            losses.append(loss.item())

        # Every C steps reset Q_hat=Q
        if epoch % C == 0:
            target_network.load_state_dict(q_network.state_dict())

        epoch += 1
        if (epoch % 10_000 == 0) and epoch > 0:
            smoothed_reward = np.mean(rewards) if rewards else 0
            smoothed_rewards.append(smoothed_reward)
            total_rewards_list.append(rewards)
            rewards = []

            loss_mean = np.mean(losses) if losses else 0
            loss_means.append(loss_mean)
            total_loss_list.append(losses)
            losses = []

        if (epoch % 100_000 == 0) and epoch > 0:
            plt.plot(smoothed_rewards)
            plt.title("Average Reward on Breakout")
            plt.xlabel("Training Epochs [units of 10,000]")
            plt.ylabel("Average Reward per Episode")
            if not os.path.exists('./Imgs'):
                os.makedirs('./Imgs')
            plt.savefig(f'./Imgs/average_reward_on_breakout_{epoch}.png')
            # plt.show()
            plt.close()

            plt.plot(loss_means)
            plt.title("Average Loss on Breakout")
            plt.xlabel("Training Epochs [units of 10,000]")
```

```
            plt.ylabel("Average Loss per Episode")
            if not os.path.exists('./Imgs'):
                os.makedirs('./Imgs')
            plt.savefig(f'./Imgs/average_loss_on_breakout_{epoch}.png')
            # plt.show()
            plt.close()

            print(f"Epoch: {epoch}, Loss: {loss_mean}, Smoothed Reward:
{smoothed_reward}")

        if epoch % 500_000 == 0 and epoch > 0:
        # if epoch % 10_000 == 0 and epoch > 0:
            checkpoint_path = f'./checkpoints/ddqn_checkpoint_{epoch}.pth'
            if not os.path.exists('./checkpoints'):
                os.makedirs('./checkpoints')
            if not os.path.exists('./checkpoint_data'):
                os.makedirs('./checkpoint_data')
            torch.save(q_network.state_dict(), checkpoint_path)

            # Save smoothed rewards
            with open(f'./checkpoint_data/total_rewards_list_{epoch}.pkl', 'wb') as f:
                pickle.dump(total_rewards_list, f)

            # Save losses
            with open(f'./checkpoint_data/total_loss_list_{epoch}.pkl', 'wb') as f:
                pickle.dump(total_loss_list, f)

        progress_bar.update(1)
    rewards.append(total_rewards)

    if total_rewards > best_reward:
        best_reward = total_rewards
        if not os.path.exists('./best_models'):
            os.makedirs('./best_models')
        torch.save(q_network.cpu(), f'./best_models/best_model_{best_reward}')
        q_network.to(device)

def evaluation(reward, visual=True, num_episode=10):
    # Initialize environment
    if visual:
        env_display = gym.make("ALE/Breakout-v5", render_mode="human")
    else:
        env_display = gym.make("ALE/Breakout-v5")
    env_display = gym.wrappers.RecordEpisodeStatistics(env_display)
```

```
env_display = gym.wrappers.ResizeObservation(env_display, (84, 84))
env_display = gym.wrappers.GrayscaleObservation(env_display)
env_display = gym.wrappers.FrameStackObservation(env_display, 4)
env_display = MaxAndSkipEnv(env_display, skip=4)

obs, info = env_display.reset()
rewards = []
total_rewards = 0
steps = 0

# Load the trained model
best_model_path = f"./best_models/best_model_{reward}"

best_model = torch.load(best_model_path, map_location="cuda")
best_model = best_model.to("cuda")
best_model.eval()
print(f"Episode Start")

for episode in range(num_episode):
    print(episode)
    obs, info = env_display.reset()
    dead = False
    total_rewards = 0
    steps = 0

    while not dead:
        current_life = info['lives']
        with torch.no_grad():
            obs_tensor = torch.tensor(obs, dtype=torch.float32).unsqueeze(0).to("cuda")
            q_values = best_model(obs_tensor)
            action = torch.argmax(q_values, dim=1).item()  # Get action with max Q-value

        if steps == 0 or terminated or truncated:
            action = 1

        obs, reward, terminated, truncated, info = env_display.step(action)
        # print(action)
        dead = terminated or truncated
        total_rewards += reward
        steps += 1
        if visual:
            done = np.array(info['lives'] < current_life)
            if done:
                print("life -1")
```

```
            if reward != 0:
                print(f'Steps: {steps}, Reward: {reward}')
            if terminated or truncated:
                print(f"Episode finished. Total rewards: {total_rewards}")
        rewards.append(total_rewards)
    mean_reward = np.mean(rewards)
    std_reward = np.std(rewards)
    print(mean_reward)
    # plt.plot(rewards)
    plt.plot(range(0, len(rewards)), rewards, label='Rewards per Episode')
    plt.axhline(y=mean_reward, color='r', linestyle='--', label=f'Mean: {mean_reward:.2f}, Std:
{std_reward:.2f} ')
    plt.title("Best Model Reward on Breakout")
    plt.xlabel("Testing Epochs")
    plt.ylabel("Reward per Episode")
    if not os.path.exists('./Imgs'):
        os.makedirs('./Imgs')
    plt.legend()
    plt.show()
    plt.savefig(f'./Imgs/best_model_reward_on_breakout.png')
    plt.close()
    env_display.close()
    print(f"Evaluation completed.")

if __name__ == "__main__":
    script_dir = os.path.dirname(os.path.abspath(__file__))
    os.chdir(script_dir)
    # Breakout Game Initialisation
    gym.register_envs(ale_py)
    env = gym.make("ALE/Breakout-v5")

    env = gym.wrappers.RecordEpisodeStatistics(env)
    env = gym.wrappers.ResizeObservation(env, (84, 84))
    env = gym.wrappers.GrayscaleObservation(env)
    env = gym.wrappers.FrameStackObservation(env, 4)
    env = MaxAndSkipEnv(env, skip=4)
    Deep_Q_Learning(env, buffer_size=100_000, nb_epochs=5_000_000,
exploration_steps=100_000, replay_start_size=5_000, device='cuda', C=1_000)
    Deep_Q_Learning(env, buffer_size=100_000, nb_epochs=5_000_000,
exploration_steps=1_000_000, replay_start_size=50_000, device='cuda', C=10_000)
    best_rewards = 67.0
    evaluation(best_rewards, False, 1000)
```

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