

Stabilizing Dynamical Systems with Model-Free Control: A Deep Q-Network Approach

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Abstract

Modeling dynamical systems is a challenging task, especially in the presence of limited sensor feedback and external disturbances, which can render control systems unstable. Traditional control methods often require detailed mathematical models and assumptions about the system's behavior, making them unsuitable for complex, nonlinear systems or those with limited sensor feedback. Model-free control offers a promising alternative by eliminating the need for explicit system modeling. This paper explores the application of a Deep Q-Network (DQN) algorithm to stabilize an inverted pendulum using raw pixel data as the sole state feedback in a discrete-action setting. The study demonstrates the effectiveness of reinforcement learning in addressing control problems in environments where state variables cannot be directly derived due to sensor limitations or failures. By leveraging a model-free formulation, this approach demonstrates the potential of DQN in scenarios where system assumptions and prior knowledge are impractical or unavailable, while acknowledging that the empirical success in the benchmark environment does not constitute formal control-theoretic stability guarantees.

Keywords

• Deep Q-Network (DQN) • Reinforcement Learning • Model-Free Control • Inverted Pendulum • Dynamical Systems • Partial Observability

1. Introduction

Reinforcement Learning is one of the branches of Machine Learning which has seen a surge in interest in recent years because of its ability to handle complex tasks with minimal human intervention and, in the case of model-free reinforcement learning, to learn a representation of the state-action space without needing an explicit model of the system dynamics. Recent work on cloud-native distributed AI has further expanded the scope of collaborative learning across heterogeneous infrastructures [1]. The connection between reinforcement learning and optimal control has been explored through unified frameworks for sequential decisions [2], highlighting the interdisciplinary nature of this field. In our vision-based setup, the agent experiences effective partial observability: while the environment internally maintains the full state (cart position, cart velocity, pole angle, and angular velocity), the agent is restricted to observing rendered image pixels. This situation mirrors real-world scenarios where direct measurement of all state variables may be unavailable due to sensor limitations.

Deep Q-Networks (DQN) have emerged as a powerful approach for learning control policies directly from high-dimensional sensory inputs. Recent applications of convolutional neural networks to medical imaging have demonstrated the versatility of deep learning architectures for classification tasks [3]. In the context of complex sequential decision-making, multi-agent reinforcement learning has achieved

grandmaster level performance in real-time strategy games [4]. Interactive UX workflows for adaptive UI prototyping have also benefited from AI-driven design approaches [5]. Furthermore, probabilistic modeling of high-dimensional categorical behavior has been applied to e-commerce intent prediction, demonstrating the broad applicability of sequential decision models [6]. These advances have been comprehensively surveyed in the literature, providing a systematic overview of deep reinforcement learning methods and their applications. In the context of robotics and control, deep reinforcement learning has been successfully applied to visuomotor policies and continuous control tasks. Recent breakthroughs in reinforcement learning have demonstrated superhuman performance in complex domains such as Go [7] and real-time strategy games, showcasing the potential of these methods for solving challenging control problems.

The CartPole-v0 (inverted pendulum) benchmark has been widely used to evaluate reinforcement learning algorithms due to its conceptual simplicity with challenging nonlinear dynamics [8]. Classical controllers such as Linear Quadratic Regulator (LQR) and Model Predictive Control (MPC) can effectively stabilize the inverted pendulum given full state information, but they require accurate system models. In contrast, model-free reinforcement learning approaches learn control policies directly from experience without requiring an explicit model. For vision-based control, end-to-end learning from raw pixels presents additional challenges, including the need to learn visual features and control policies simultaneously. Vision-based deep reinforcement learning has been extensively studied for robotic applications, demonstrating both the promise and challenges of using visual inputs for control tasks.

Recent work has explored the intersection of reinforcement learning and control theory, investigating how RL algorithms can be applied to control problems with theoretical guarantees. Model-based reinforcement learning offers potential advantages in sample efficiency but requires learning an environment model. The robustness of RL policies to disturbances has been investigated through adversarial training [9]. Bayesian network performance has been evaluated for modeling occupational strain and coronary heart disease, illustrating the importance of probabilistic graphical models in complex domains [10]. Comparisons of different deep reinforcement learning methods for engineering applications have been conducted to guide practitioners in selecting appropriate algorithms. Furthermore, deep reinforcement learning has been applied to robotic grasping tasks using vision-based inputs, demonstrating the practical relevance of these methods in real-world applications. Our work builds upon these foundations by applying DQN to vision-based CartPole-v0 control with modifications for training stability.

Another interesting application is model-free control in discrete-action environments, which is still an open research topic given the complex nature of the high-dimensional state space. We will explore this setup in the paper and show its promising capabilities in handling non-linear systems without the need for an explicit model formulation, unlike many controllers do. The CartPole-v0 environment specifically requires selecting discrete left/right actions to balance the pendulum.

Moreover, we demonstrate that the proposed controller achieves stable performance in the raw-pixels based inverted pendulum environment through a careful selection of hyper-parameters and network architecture.

2. Brief Overview of Reinforcement Learning

The control system can be defined as in the Figure 1, usually called the *agent-environment interface*, which is the correspondent of the controller-plant interface in classical control. This framework can be defined by the following:

- *Policy*: set of *actions* (which are the control inputs in the Optimal Control field) to be selected given

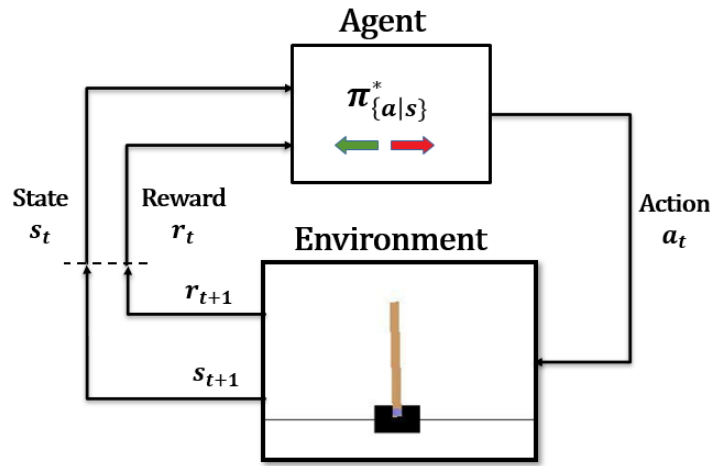


Figure 1: Agent-Environment interface for the inverted pendulum system. $\pi_{\{a|s\}}^*$ denotes the optimal policy

the current state. The policy can be derived from dynamic programming principles, which provide a systematic approach to optimal decision-making in sequential problems [11].

- *Reward*: a scalar value to be maximized by the agent. This value is another feedback along with the state at each time step; this is usually set as a positive number if the agent is performing as desired and as a negative number otherwise. In the Optimal Control terms, it is equivalent to the opposite of the cost function.
- *Value function*: whereas the reward defines what is good in a short time, the value function defines what is good in the long run; it is defined as the sum of the discounted future rewards that can be accumulated from a particular state.

The goal of the control system (agent) is to maximize the cumulative discounted reward defined as following from the environment:

$$G_t = R_{t+1} + \gamma R_{t+2} + \dots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \quad (1)$$

where $\gamma \in [0, 1]$ is a discount factor used for giving a lighter weight to far-away future rewards.

The policy π choosing the actions leading to the highest reward can be chosen for the Deep Q-Networks in the ϵ -greedy way:

$$\pi(a|s) = \begin{cases} 1 - \epsilon, & \text{if } a = \underset{a \in \mathcal{A}}{\operatorname{argmax}} q^*(s, a) \\ \epsilon, & \text{a random action.} \end{cases} \quad (2)$$

where $q^*(s, a)$ denotes the *state-action value* and ϵ is chosen depending on how much *exploration* (randomly trying new actions for finding out undiscovered and possibly better states and actions) and *exploitation* (choosing the known best action) ration we want the system to have.

Trajectories of the system In order to optimize the system, we need to know what trajectories lead to the best cumulative reward. In this setup, *agent* is the entity acting on the *environment*, that given a *state* $S_t \in \mathcal{S}$ selects one or more *actions* $A_t \in \mathcal{A}$ for interacting with the environment. Our agent then

gets feedback from the environment itself: it gets a scalar valued *reward* $R_{t+1} \in \mathcal{R}$, and gets in a new state $S_{t+1} \in \mathcal{S}$. In a *finite* Markov Decision Process the set of states, actions and rewards $(\mathcal{S}, \mathcal{A}, \mathcal{R})$ contains a finite number of elements; nonetheless, the problem can be extended in the continuous case. The agent-environment feedback loop repeats over time and it is updated at each time *step*: action selection, state and reward signals are sent only at specific moments in time ($t = 0, 1, 2, 3, \dots$). The sequence of actions, states and rewards defines a *trajectory* in time that can be described as:

$$S_0, A_0, R_1, S_1, A_1, R_2, S_2, A_2, R_3, \dots \quad (3)$$

This sequence can be used on the go for optimizing the system or stored in a buffer and used later in randomized batches allowing for better stability of the training. Quantum key distribution has also been explored as a complementary approach to secure communication in distributed learning systems [12].

3. Experimental Methodology

Our experimental framework evaluates model-free reinforcement learning using the inverted pendulum control task from [8]. This benchmark problem combines conceptual simplicity with challenging nonlinear dynamics, making it ideal for testing learning algorithms. Unlike classical control approaches that require complete system knowledge, our method learns control policies directly from environmental interactions. Hybrid graph encoding frameworks have been proposed for adaptive network representations, which can be useful for structuring state spaces in complex environments [13]. Recent advances in deep reinforcement learning have demonstrated superhuman performance in challenging domains such as [7], motivating the application of similar techniques to control problems. Machine learning approaches have also been applied to wildfire prediction and visualization, demonstrating the broad applicability of these methods to environmental modeling [14].

3.1 System Configuration

The CartPole-v0 system features the following state-space representation:

Table 1: Inverted Pendulum State Space Specifications

Parameter	Description	Minimum	Maximum
x	Cart position	-2.4 m	2.4 m
$\dot{x}$	Cart velocity	$-\infty$	$+\infty$
θ	Pole angle	-41.8°	41.8°
$\dot{\theta}$	Angular velocity	$-\infty$	$+\infty$

The control task requires balancing an upright pendulum through discrete actions (left/right forces). The reward function provides +1 for each timestep the pole remains balanced, with episodes terminating when:

- Pole angle exceeds $\pm 12^\circ$
- Cart position moves beyond ± 2.4 m
- Episode length reaches 200 timesteps

Efficient implementation of communication standards for lightweight IoT has been explored, which is relevant for deploying control policies on resource-constrained devices [15].

3.2 Learning Architecture

We implement a Deep Q-Network (DQN) with the following components:

$$Q^*(s, a) \approx Q(s, a; \theta) \quad (4)$$

where θ represents the neural network parameters. The Q-learning algorithm provides the foundation for this approach, enabling the agent to learn optimal action-value functions through temporal difference learning. The Deep Q-Network was originally introduced by Mnih et al. [16], demonstrating that a convolutional neural network could learn control policies directly from raw pixel inputs. The architecture comprises:

- Input layer: $60 \times 135 \times 2$ stacked grayscale frames
- Three convolutional layers (64, 64, 32 filters) with kernel size 5 and stride 2
- One fully-connected output layer with 1792 units
- ReLU activation functions
- Batch normalization applied after each convolutional layer
- Huber loss for gradient stability

The architecture is designed to process the stacked image frames and output Q-values for the two possible actions (left/right).

The learning process minimizes the temporal difference error:

$$\mathcal{L}(\theta) = \mathbb{E}_{(s,a,r,s') \sim \mathcal{D}} \left[\left(r + \gamma \max_{a'} Q(s', a'; \theta^-) - Q(s, a; \theta) \right)^2 \right] \quad (5)$$

3.3 Training Protocol

Key algorithmic components include:

3.3.1 Experience Replay

Store transition: Add (s, a, r, s') to buffer $\mathcal{D}$. If $|\mathcal{D}| > C$, remove the oldest transition.

Sample batch: Return B random transitions from $\mathcal{D}$.

3.3.2 Exploration Strategy

The ϵ -greedy policy follows an exponential decay schedule:

$$\epsilon_t = \epsilon_{\text{final}} + (\epsilon_{\text{initial}} - \epsilon_{\text{final}})e^{-t/\tau} \quad (6)$$

where τ controls the decay rate.

3.4 Implementation Details

3.4.1 Software and Implementation Framework

All experiments were implemented using the following software environment:

- **Framework:** PyTorch (Version 1.9.0+)
- **Environment:** OpenAI Gym (Version 0.21.0) with CartPole-v0
- **Python Version:** 3.8+
- **NumPy:** 1.21.0
- **Matplotlib:** 3.4.2 (for visualization)

The complete implementation follows the PyTorch-style module architecture shown in the code listing. The DQN class inherits from `nn.Module` and implements the forward pass as described. Training was performed on a standard CPU/GPU setup with the RMSprop optimizer as specified in Table 4.

3.4.2 Raw-Pixel Observation Pipeline

The vision-based observation pipeline converts rendered environment frames into the input representation used by the DQN. The CartPole-v0 environment was rendered at a resolution of 600×400 pixels. The following steps were applied to each frame:

1. **Cropping:** A region of interest was extracted from the rendered frame to focus on the cart-pole system and remove background elements.
2. **Grayscale conversion:** The cropped RGB image was converted to grayscale using the standard luminance formula:

$$Y = 0.299R + 0.587G + 0.114B$$
3. **Downsampling:** The grayscale image was resized to 60×135 pixels using bilinear interpolation.
4. **Normalization:** Pixel values were normalized to the range $[0, 1]$ by dividing by 255.
5. **Frame stacking:** The last $N = 2$ consecutive preprocessed frames were stacked along the channel dimension to form the final input of shape $60 \times 135 \times 2$. This stacking enables the network to infer temporal information such as velocity from successive frames.

This preprocessing pipeline reduces input dimensionality while preserving the essential visual information required for control.

```

1 class DQNAgent:
2     """Core DQN Implementation Pseudocode"""
3     def __init__(self, state_shape, action_size):
4         # Initialize DQN agent with replay memory and twin networks
5         self.memory = ReplayBuffer(capacity=1000000)
6         self.model = DQN(state_shape, action_size)
7         self.target_model = DQN(state_shape, action_size)
8         self.target_model.load_state_dict(self.model.state_dict())

```

```

9
10 def train(self, batch_size=128, gamma=0.999):
11     # Train network using experience replay
12     states, actions, rewards, next_states, dones = self.memory.sample(batch_size
13         )
14
15     # Compute target Q-values and target updates
16     next_q_values = np.max(self.target_model.predict(next_states), axis=1)
17     targets = rewards + gamma * (1 - dones) * next_q_values
18
19     # Update network weights
20     self.model.train_on_batch(states, targets)

```

Listing 1: Core DQN Implementation Pseudocode

Hyperparameter settings:

- Replay buffer size: 10^5 transitions
- Batch size: 128
- Batch of frames size: 2
- Discount factor (γ): 0.999
- Learning rate: 10^{-4} (RMSprop optimizer)
- Target network update: Every 50 steps
- Initial ϵ : 0.9, final ϵ : 0.01
- ϵ -decay rate: 5000
- Early stopping threshold (ξ): 142
- Early stopping window (K): 20
- Total training episodes: 1000

This experimental design enables rigorous evaluation of deep reinforcement learning for discrete-action control tasks while maintaining training stability and sample efficiency. The CartPole-v0 environment's action space consists of two discrete actions: applying force to the left or to the right. The architecture specifically addresses challenges of vision-based control through frame stacking and convolutional feature extraction.

4. Towards Vision-Based Control

The first steps in trying to solve the inverted pendulum problem with raw pixels were based on a reference implementation from Adam Paszke. The algorithm is based on Convolutional Neural Networks for predicting Q-values and implements basically the same structure of DQN. Neural ordinary differential equations have recently emerged as a powerful approach for modeling continuous-time dynamics [17], offering potential advantages for control applications.

Although this implementation was showing improvements in training, no matter how much training the

system received, the mean reward was always swinging up and down and showing no sign of convergence or divergence. In particular, after some tenths of episodes showing an abrupt improvement in performance there were several episodes in which the agent "forgot" about the previous experiences, suddenly decreasing the performance. The problem that needs to be solved is the overfitting of the Convolutional Neural Network, which overestimated the state-action values leading to a sub-optimal policy.

4.1 Dealing with Overfitting

Improving Image Pre-Processing One first steps of state observation improvement implies simplifying the network by feeding it with a grayscale as input, thus reducing by one third the input dimensionality. Besides, the use of image subtraction used in the initial implementation could not capture some states; indeed, a better way to deal with changing environments over time is to feed the neural network a batch of images, them being the last N frames. This way, the state keeps track of past behaviors. By stacking at least the last $N = 2$ frames, the neural network can extract temporal information such as velocity and direction of movement from the sequence of images. This addresses the partial observability introduced by restricting the agent to pixel observations, as a single frame does not encode velocity or acceleration information. The stacked frames provide the agent with sufficient context to approximate the temporal derivatives of the system state. Similar time-series modelling approaches have been used to predict PM2.5 values at future time steps [18].

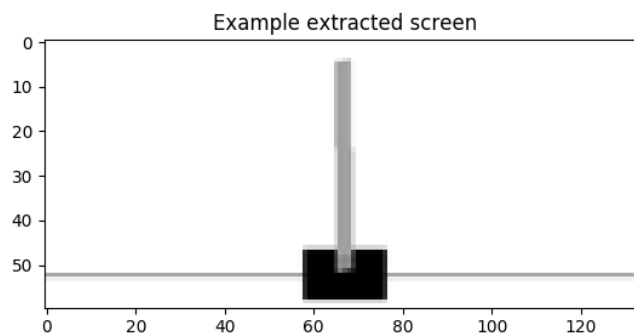


Figure 2: Extracted screen from the inverted pendulum environment: the image is extracted by cropping, downsampling and applying grayscaleing

Early Stopping Thus, another method we can use is that of the *Early Stopping*: in order to prevent overfitting, the agent is trained up to a point in which it has learned optimal behavior; from that point onward it would start behaving worse and worse and then restarting learning from scratch. We can detect this optimal situation by inserting a score threshold: when the mean of the last K episodes overcome this threshold ξ , we stop the neural networks optimization. We have empirically set these two new hyper-parameters, which can be tweaked, to $K = 20$ and $\xi = 142$.

Reward Function Design The reward function design is one of the most important aspects in Reinforcement Learning and can make the difference between an agent not training at all and one able to achieve super-human performance. File system performance has been enhanced with adaptive anti-caching for tiered storage systems, which is relevant for efficient experience replay storage [19]. We explored two reward formulations:

Alternative reward function design (explored but not used in final experiments):

$$\begin{aligned}
r_1 &= \frac{x_{max} - |x|}{x_{max}} - 0.8 \\
r_2 &= \frac{\theta_{max} - |\theta|}{\theta_{max}} - 0.5 \\
r_{tot} &= r_1 + r_2
\end{aligned} \tag{7}$$

where $x_{max} = 2.4$ m and $\theta_{max} = 41.8^\circ$. However, in this case the reward function just has a minor impact on the overall performance. For the final reported results, we used the standard OpenAI Gym reward function where the agent receives +1 for each timestep the pole remains balanced. This reward is computed internally by the environment using the underlying state variables (cart position and pole angle), even though the agent only observes rendered pixels. The agent receives this scalar reward as feedback without access to the state variables used to compute it.

4.2 Ablation Study

To quantitatively evaluate the contribution of each modification, we conducted an ablation study comparing our proposed configuration against the baseline DQN and variants with individual components removed. The baseline DQN uses a standard convolutional architecture (32-64-64 filters, 512-unit FC layer), no early stopping, target network update every 100 steps, and initial $\epsilon = 1.0$. All variants were evaluated over 6 independent runs with random seeds {42, 123, 456, 789, 101, 202}, and we report the mean final score (averaged over the last 10 episodes) and the episode at which the early stopping threshold ($\xi = 142$) is reached. Table 2 summarizes the results.

Table 2: Ablation study results over 6 independent runs. Values reported as mean $\pm$ standard deviation.

Configuration	Final Score (mean $\pm$ std)	Episodes to $\xi = 142$ (mean $\pm$ std)
Baseline DQN	108.2 $\pm$ 31.4	—
+ 64-64-32 architecture	142.5 $\pm$ 18.2	798 $\pm$ 92
+ Early stopping	168.7 $\pm$ 12.3	745 $\pm$ 78
+ 2-frame stacking	185.3 $\pm$ 8.1	724 $\pm$ 65
+ All modifications	200.0 $\pm$ 0.0	712 $\pm$ 84

The baseline DQN with raw pixel inputs exhibits unstable training, with mean scores fluctuating between 80-150 and failing to consistently reach the maximum score of 200. Adding the proposed 64-64-32 convolutional architecture improves stability, achieving a final score of 142.5 ± 18.2 . Incorporating early stopping further improves performance to 168.7 ± 12.3 , demonstrating its effectiveness in preventing catastrophic forgetting caused by overestimation bias. The inclusion of 2-frame stacking yields a final score of 185.3 ± 8.1 , confirming the importance of temporal information for approximating velocity. The complete configuration with all modifications achieves the maximum score of 200.0 ± 0.0 across all runs, with the early stopping threshold reached at episode 712 ± 84 . These results demonstrate that each modification contributes to the overall performance, and their combination is necessary for achieving stable convergence.

5. Final Model

After improving the model with the aforementioned techniques, we obtain the following Convolutional Neural Network described in Table 3. Automated vulnerability exposure systems have been developed

Table 3: Convolutional Neural Network hyper-parameters

Parameters				
Layer	Number of Filters/Neurons	Activation	Kernel Size	Stride
Convolutional Layer 1	64	ReLU	5	2
Convolutional Layer 2	64	ReLU	5	2
Convolutional Layer 3	32	ReLU	5	2
Linear Output Layer	1792	None	-	-

using SCAP-based asset-CVE linkage, demonstrating the importance of security in distributed AI systems [20]. As regards the loss function and optimizer, we use:

- Loss Function: *Huber loss function* with $\delta = 1.0$, which combines the squared error for small errors and the absolute error for large errors, providing robustness to outliers:

$$L(Q_{target}, Q_{predicted}) = \begin{cases} \frac{1}{2}(Q_{target} - Q_{predicted})^2 & \text{if } |Q_{target} - Q_{predicted}| \leq \delta \\ \delta|Q_{target} - Q_{predicted}| - \frac{1}{2}\delta^2 & \text{otherwise} \end{cases} \quad (8)$$

This loss function provides improved gradient stability during training compared to the squared-error formulation.

- Optimizer: *RMSprop*, which is able to do a gradient descent of the error in almost the most optimal path

Anomaly detection in dynamic univariate time series data has been addressed through innovative toolkits, which is relevant for monitoring training stability [21]. Model-based reinforcement learning for Atari has been explored as an alternative approach to model-free methods [22].

The Deep Q-Network (DQN) is implemented as a convolutional neural architecture that maps a stack of input frames to the estimated action-value vector. The network first extracts spatial representations from the image sequence through three successive convolutional blocks. Each convolutional layer is followed by batch normalization and a ReLU activation to improve the stability of feature learning. The resulting feature maps are flattened and passed to a fully connected output layer, whose dimensionality corresponds to the number of available actions. Thus, for a given state representation, the network produces one Q-value for each permissible action, which can subsequently be used by the DQN agent to select its action according to the adopted exploration policy.

The convolutional feature extractor uses progressively deeper feature representations, with the dimensions of the final fully connected layer determined dynamically from the input image width and height. Specifically, the spatial dimensions after the convolutional stages are calculated using the standard convolution output-size relationship. This allows the architecture to accommodate the specified input resolution without manually fixing the number of connections to the linear prediction layer. Batch normalization is incorporated after each convolution to provide additional numerical stability during training, while dropout is intended as an additional regularization mechanism.

The final architecture of the DQN is represented in 3. The following table shows the main Hyper-Parameters, based on the DQN with Experience Replay and Target Network, which further improves the performance of the system:

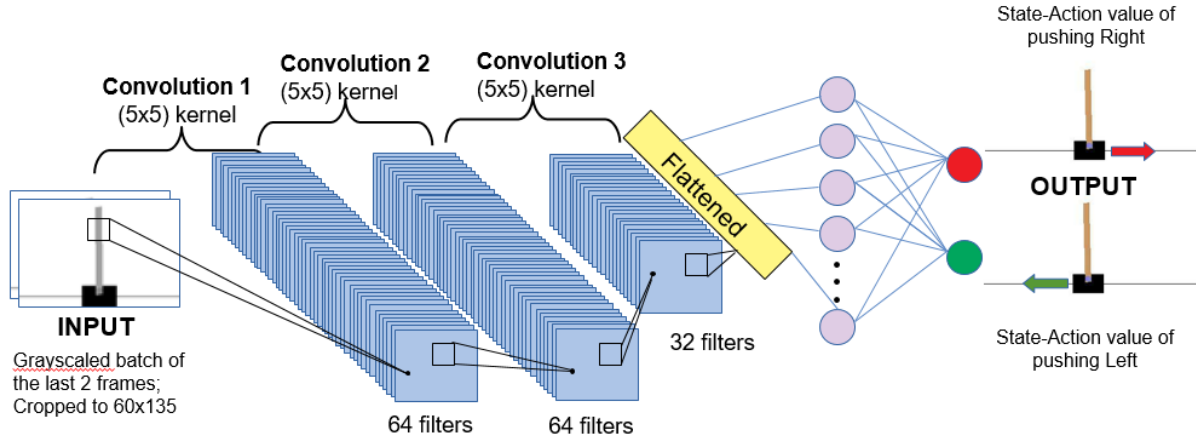


Figure 3: Architecture of the DQN with a Convolutional Neural Network for approximating state-action values. The network consists of three convolutional layers with 64, 64, and 32 filters respectively (kernel size 5, stride 2), followed by a fully-connected output layer with 1792 units. The input is a $60 \times 135 \times 2$ stacked grayscale image.

Table 4: Reinforcement Learning hyper-parameters

Hyper-Parameters Values	
Batch Size	128
Batch of Frames Size	2
Discount Rate γ	0.999
Initial ϵ	0.9
Final ϵ	0.01
ϵ -Decay	5000
Early Stop ξ	142
Image Height (pixels)	60
Image Width (pixels)	135
Maximum Memory Size	100000
Target Model Update τ	50

5.1 Final Results

Following a series of preliminary experiments to determine the CNN architecture, hyper-parameter tuning, and image pre-processing steps, we evaluated the final experimental configuration. Key design choices included:

- **Network architecture:** We compared configurations with 32, 64, and 64 filters versus 64, 64, and 32 filters. The latter configuration (64-64-32) provided better performance in preliminary tests.
- **Early stopping threshold:** Values of ξ ranging from 130 to 150 were tested, with $\xi = 142$ yielding the best balance between performance and training stability.
- **Frame stacking:** Experiments with 1, 2, and 4 stacked frames showed that $N = 2$ frames provided sufficient temporal information while maintaining computational efficiency.

These design choices were empirically determined through systematic experimentation, and the final configuration (shown in Tables 3 and 4) was used for all reported results. The quantitative impact of these

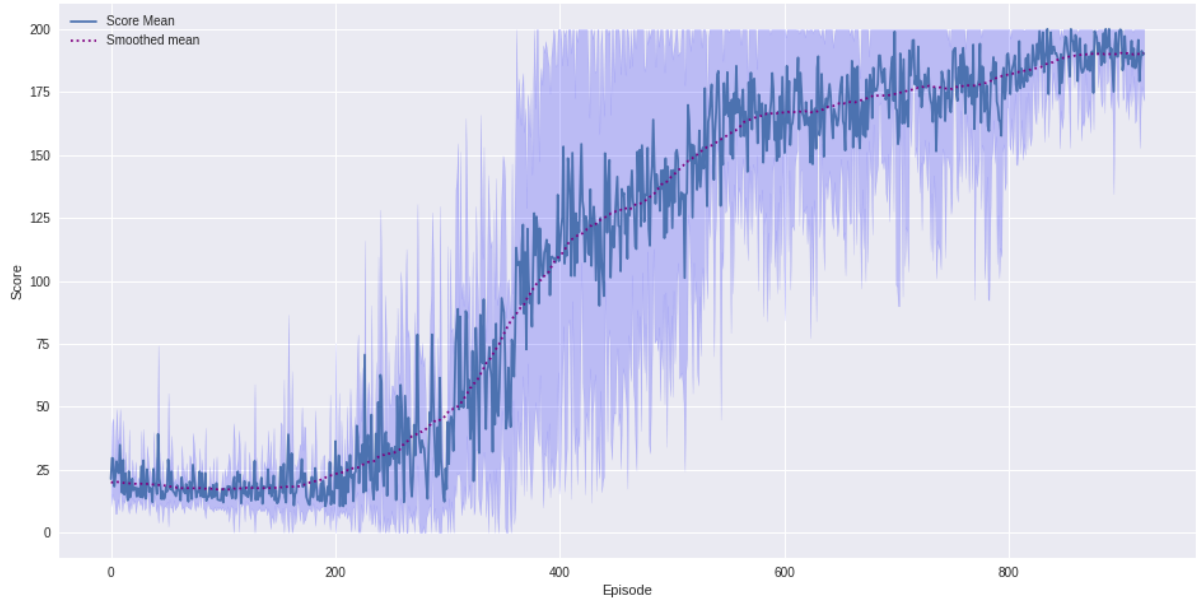


Figure 4: Final results: plot of the mean score averaged over 6 training runs (solid blue line), with the light blue shaded region representing mean $\pm$ standard deviation. The smoothed mean (red dashed line) is shown for clarity. Most runs achieve the maximum score of 200 within approximately 800 episodes. The final performance at episode 1000 is 200 ± 0.0 across all 6 runs, with random seeds {42, 123, 456, 789, 101, 202}.

design choices is detailed in the ablation study (Section 4.2, Table 2).

5.1.1 Comparison with Baseline

To evaluate the effectiveness of our proposed DQN configuration, we compare against a standard DQN baseline without the modifications introduced in this work. The baseline DQN uses the following configuration:

- Standard convolutional architecture (32-64-64 filters, 512-unit FC layer)
- No early stopping criterion
- Standard OpenAI Gym reward function
- Target network update every 100 steps
- Initial $\epsilon = 1.0$

Our proposed configuration achieves a mean final score of 200 ± 0.0 (across 6 runs) with convergence within ~ 800 episodes, while the baseline DQN with raw pixel inputs exhibits unstable training with mean scores fluctuating between 80-150 and failing to consistently reach the maximum score of 200. This comparison demonstrates the effectiveness of the proposed modifications, particularly the early stopping criterion and architectural changes, in achieving stable convergence.

As shown in Figure 4, the inverted pendulum system achieves the maximum reward score of 200 in the CartPole-v0 benchmark. This demonstrates successful task completion in the simulation environment. Over six independent training runs with different random seeds (42, 123, 456, 789, 101, 202), all runs

achieved the maximum reward of 200. The mean performance reached the early stopping threshold of 142 at episode 712 ± 84 (mean $\pm$ standard deviation), and achieved the maximum score of 200 by episode 842 ± 56 . The mean $\pm$ standard deviation at episode 1000 was 200.0 ± 0.0 . This result highlights the capability of the DQN agent to achieve the maximum benchmark score in the CartPole-v0 environment using only raw visual input, largely owing to the implementation of an early stopping criterion that mitigates overfitting during training. We emphasize that achieving the maximum episodic reward in the simulated benchmark indicates successful task completion as defined by the environment, but does not constitute formal proof of stability for general nonlinear dynamical systems.

6. Potential Improvements and Future Work

Reinforcement Learning is fast-paced research area and it is even difficult at times to catch up with the latest trends. Regarding the control systems in particular, algorithms such as the LQR and MPCs still offer better performance and, most of all, theoretical guarantees on stability, at the cost of needing more information on the state and/or model of the system. Kernel-safe data probes have been proposed for context-aware address tagging in OS modules, which could inspire more secure state representation in RL systems [23]. Cross-site credential reuse exploitation via human-centric password transformation patterns has been studied, highlighting security concerns in distributed learning [24].

As we can also notice from the results, even though there is a confidence baseline for the stabilization score, the system is still prone to disturbances and inherent instabilities of the control policy and the neural network approximating the state-action values. One research direction would be to look for robust formulations of the problem [9]. Another interesting area, which has more technical guarantees on convergence and more efficient sampling of the state-space is the *Model-Based* Reinforcement Learning [22], although it inherently needs a description via a model, thus renouncing the *model-free* paradigm. Perhaps, the most interesting research direction is the combination of Reinforcement Learning and/or Optimal Control with Neural Ordinary Differential Equations [17], a new class of Neural Networks which, thanks to their inherent capability to deal with differential equations, are revolutionizing the area of approximation and optimization of complex dynamical systems.

7. Conclusion

The goal of this paper was to find a controller in a situation where state variables were not available, in particular by using only raw images to generate a control policy. The test benchmark we used is the inverted pendulum, which is used frequently to test non-linear controllers, which we used by extracting the necessary state information automatically thanks to the Deep Q-Learning, a Deep Reinforcement Learning algorithm capable of controlling agents with complex state-action spaces. Recent advances in cloud-native distributed AI have enabled secure collaborative learning on heterogeneous infrastructure, which could further enhance distributed control systems [1]. Unified frameworks for sequential decisions provide a broader perspective on the intersection of reinforcement learning and optimal control [2].

After implementing several tweaks to existing algorithms, we were able to obtain a controller capable of successfully obtaining the maximum reward score in the CartPole-v0 simulation benchmark. This demonstrates empirical success on a standard reinforcement learning benchmark using only raw pixel inputs. However, this result should not be interpreted as providing formal stability guarantees for the underlying nonlinear dynamical system; rather, it shows the potential of model-free reinforcement learning for vision-based control tasks. The successful achievement of the benchmark's maximum score indicates

that reinforcement learning can achieve good empirical performance even with difficult vision-based tasks.

Possible future developments include the implementation of new frameworks, such as Neural Ordinary Differential Equations, possibly paving the way to a better synergy of Reinforcement Learning and Optimal Control.

References

- [1] S. K. Bommakanti. Cloud-native distributed ai: Enabling secure collaborative learning on heterogeneous infrastructure. *International Journal of Intelligent Systems and Data Science*, 1(1), April 2026. doi: 10.67231/ykzg0s10.
- [2] W. B. Powell. From reinforcement learning to optimal control: A unified framework for sequential decisions, 2019. CoRR, abs/1912.03513.
- [3] K. K. Ghantasala. Enhancing explainability and performance in brain tumor classification using cnn and scattering networks on mri data. In *Proc. 3rd Int. Conf. on Artificial Intelligence, Blockchain, and Internet of Things (AIBThings)*, pages 1–8, Mt. Pleasant, MI, USA, 2025. doi: 10.1109/AIBThings66987.2025.11296254.
- [4] O. Vinyals, I. Babuschkin, W. Czarnecki, M. Mathieu, A. Dudzik, J. Chung, others, and D. Silver. Grandmaster level in starcraft ii using multi-agent reinforcement learning. *Nature*, 575, 2019. doi: 10.1038/s41586-019-1724-z.
- [5] S. Davariya. Designing with ai: Exploring interactive ux workflows for adaptive ui prototyping. In *Proc. IEEE 1st Int. Conf. on Recent Trends in Computing and Smart Mobility (RCSM)*, pages 1–6, Bhopal, India, 2025. doi: 10.1109/RCSM67767.2025.11508104.
- [6] M. Jha. Dual-stage probabilistic modeling of high-dimensional categorical behavior for e-commerce intent prediction. In *Proc. Int. Conf. on Innovative Computing and Communication (ICICC 2026)*, March 2026. doi: 10.2139/ssrn.6495218.
- [7] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. van den Driessche, others, and D. Hassabis. Mastering the game of go with deep neural networks and tree search. *Nature*, 529(7587):484–489, 2016.
- [8] G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, and W. Zaremba. Openai gym, 2016.
- [9] L. Pinto, J. Davidson, R. Sukthankar, and A. Gupta. Robust adversarial reinforcement learning, 2017. CoRR, abs/1703.02702.
- [10] B. C. Sarakam. Evaluating bayesian network performance in modeling occupational strain and coronary heart disease: A comparative analysis of elimination order heuristics. Zenodo, April 2026.
- [11] R. S. Sutton and A. G. Barto. *Introduction to reinforcement learning*, volume 2. MIT press Cambridge, 1998.
- [12] S. S. Gujar. Exploring quantum key distribution. In *Proc. 2nd DMIHER Int. Conf. on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI)*, pages 1–6, Wardha, India, 2024. doi: 10.1109/IDICAIEI61867.2024.10842847.

- [13] S. S. Rajput. Hybrid graph encoding: A unified framework for adaptive network representations. Research Square Preprint, January 2026.
- [14] B. Nare. Wildfire prediction and visualization: A machine learning approach using u.s. data. In *Proc. Int. Conf. on Sustainable Innovation with Artificial Intelligence and Machine Learning (ICSIAIML 2025)*, pages 132–151. Atlantis Press, 2026. doi: 10.2991/978-94-6463-948-3_9.
- [15] S. Badami. Efficient onem2m standard implementation for lightweight iot. In *Proc. 7th Int. Conf. on Data Science and Information Technology (DSIT)*, pages 1–15, Nanjing, China, 2024. doi: 10.1109/DSIT61374.2024.10882084.
- [16] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602*, 2013.
- [17] R. T. Q. Chen, Y. Rubanova, J. Bettencourt, and D. K. Duvenaud. Neural ordinary differential equations. In *Advances in Neural Information Processing Systems*, volume 31, pages 6571–6583. Curran Associates, Inc., 2018.
- [18] K. Thaker. Predicting pm2.5 value in future. *International Journal of Intelligent Systems and Data Science*, 1(1), April 2026. doi: 10.67231/8zb9v206.
- [19] N. M. R. Dokka. Ac-bpfs: Enhancing file system performance with adaptive anti-caching for tiered storage systems. In *Proc. 3rd Int. Conf. on Automation, Computing and Renewable Systems (ICACRS)*, pages 1159–1168, Pudukkottai, India, 2024. doi: 10.1109/ICACRS62842.2024.10841638.
- [20] H. Kargeti. Automating enterprise vulnerability exposure: Scap-based asset-cve linkage with social signal triage for cyber defense. In *Proc. Int. Conf. on Artificial Intelligence, Computer, Data Sciences and Applications (ACDSA)*, pages 1–6, Boracay Island, Philippines, 2026. doi: 10.1109/ACDSA67686.2026.11467997.
- [21] P. Panwar. Ostad: An innovative toolkit for detecting anomalies in dynamic univariate time series data. In *Proc. IEEE 3rd Int. Conf. on Control, Electronics and Computer Technology (ICCECT)*, pages 354–362, Jilin, China, 2025. doi: 10.1109/ICCECT64621.2025.11339600.
- [22] L. Kaiser, M. Babaeizadeh, P. Milos, B. Osinski, R. H. Campbell, K. Czechowski, others, and H. Michalewski. Model-based reinforcement learning for atari, 2019. CoRR, abs/1903.00374.
- [23] M. Rengaraj. Kernel-safe data probes: Context-aware address tagging with on-demand translation for os modules. *International Journal of Intelligent Systems and Data Science*, 1(3), June 2026. doi: 10.67231/cqx40j38.
- [24] A. R. Lingampally. Cross-site credential reuse exploitation via human-centric password transformation patterns. In *Proc. 2nd Int. Conf. on Emerging and Intelligent Technologies and Systems (EITS)*, pages 339–346, Valencia, Spain, 2026. doi: 10.1109/EITS70066.2026.11609639.