RUEC 2025 1st International Research Conference (IRC)

Rajshahi University Education Club, Rajshahi, Bangladesh
6th & 7th September 2025

Paper ID: 109

Topic: Intelligent Overspeed Control in Autonomous Vehicles with DQN Deep Reinforcement Learning

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Outline of Presentation

- Introduction
- Research Background
- Research Objective
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- System Architecture
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- Discussion & Implications
- Conclusion
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Introduction

- Road accidents cause 3700 deaths/ day (WHO)
- Reckless driving & over speeding in varying speed zones
- Maintaining safe speed limits across diverse environments (residential, school, highway)
- Development an intelligent speed control system to reduce road mishaps

Research Background

- Traditional speed control has limited adaptability
- Reinforcement learning is learned by interacting with the environment
- Deep Reinforcement learning uses neural networks for better performance
- Gap is that few studies address zone-specific speed control with deep Reinforcement learning

Research Objective

- We propose a Deep Q-Network (DQN) based Deep RL method.

- Goals:
  - Detect over-speeding across different zones.
  - Apply intelligent deceleration (High, mid, low).
  - Optimize vehicle speed to match zone limits.

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Methodology

- We create a 4x4 grid with zone-based speed limits (20-80km/h)
- Detect the current speed, zone speed limit, and speed difference

❑ Action Space:

  - High Deceleration (-9.8 m/s2)
  - Middle Deceleration (-5.9 m/s2)
  - Low Deceleration (-2.8 m/s2)

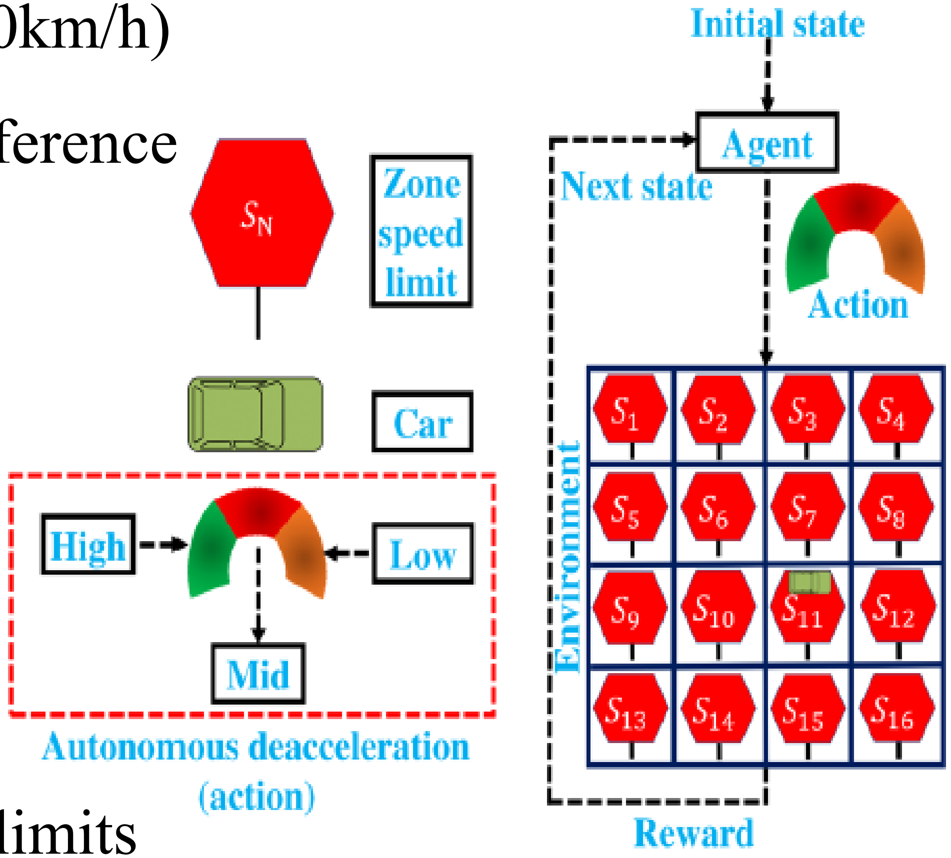

Fig. 1. Deep RL-based system overview.

- Reward Function Encourages staying within sage speed limits
- We use LSTM-based DQN for sequential state prediction

System Architecture

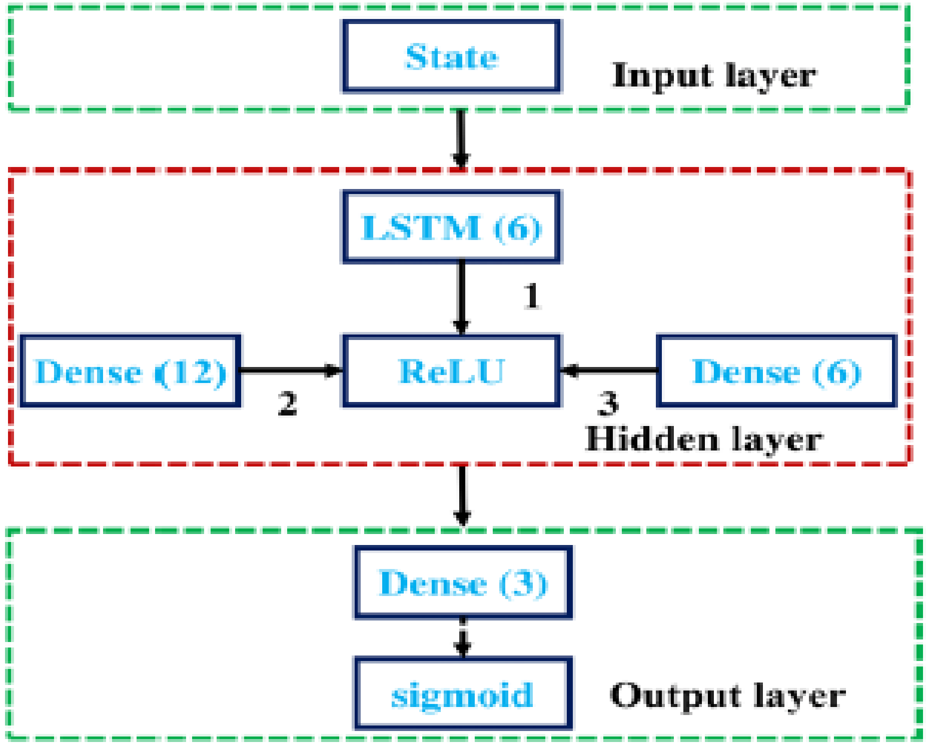

Fig. 2. Proposed deep Q-network.

TABLE II
HYPERPARAMETERS FOR TRAINING PROPOSED Q-NETWORK

Hyperparameters	Value
Optimizer	adam
Loss	categorical cross-entropy
Batch size	16
Experiences replay memory size	50
Learning rate	0.0001
Discount factor	0.9

Key Findings

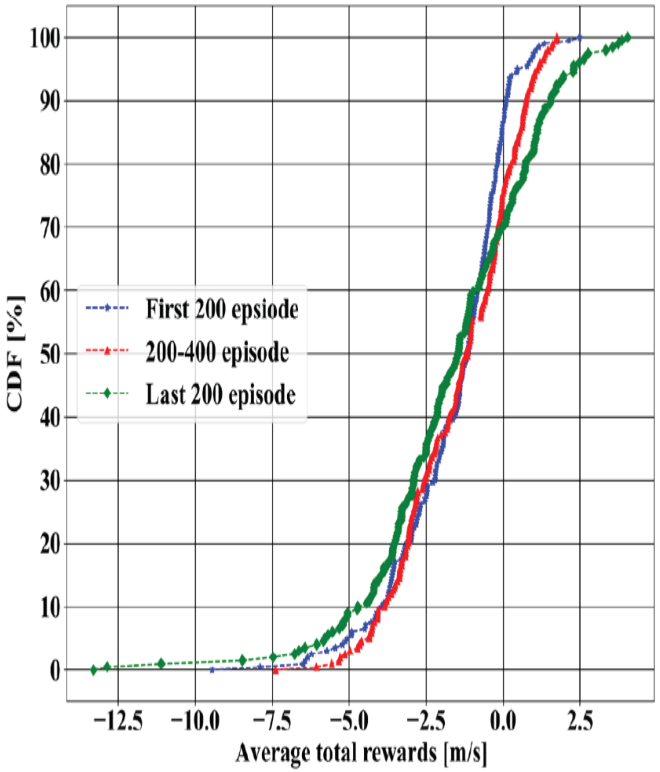

Fig. 5. CDF of average cumulative rewards.

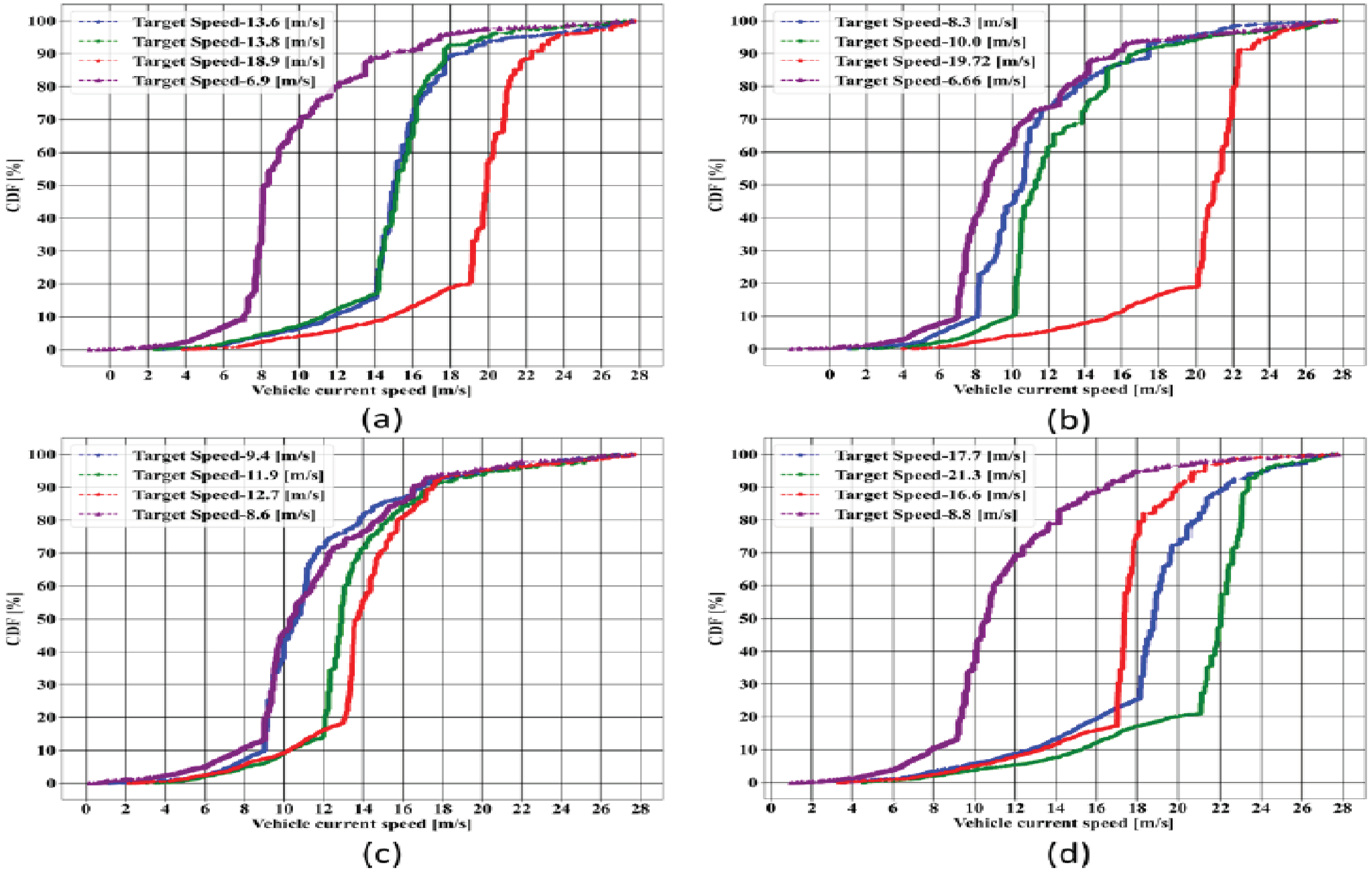

Fig. 6. CDF of current speed [m/s]

Discussion & Implications

- The proposed model successfully reduces over-speeding in diverse zones.
- DQN-based control adapts to uncertain environments
- Our contribution to demonstrate zone-specific Deep RL-Based Speed control.
- Practical Impact is that it supports safer autonomous and semi-autonomous driving systems.

TABLE I
ZONE-BASED SPEED LIMIT

Zone type	Speed limit (km/h)
Residential	20
Town	25
Rural main road	30
School and hospital	40
Constructional	45
Highways, motorways	80

Conclusion

- Road mishaps can be mitigated by **DQN-based Deep RL speed control**.
- LSTM-DQN effectively selects deceleration levels under varied conditions

Key Takeaways:

  - Dynamic speed control improves road safety.
  - Positive simulation results validate effectiveness

Future Work

- Extend the model to real-world driving datasets
- Incorporate **multi-agent learning** for complex traffic scenarios.
- Enhance with **pedestrian/collision detection modules**
- Explore real-time deployment in **autonomous vehicles**

Thank You !