

AI-driven Adaptive
Cruise Control (ACC)
Reinforcement
Learning (RL)

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ABSTRACT

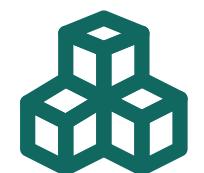
Adaptive Cruise Control (ACC) is a critical feature in modern intelligent transportation systems, enabling vehicles to maintain safe inter-vehicular distances and improve driving comfort.

Traditional ACC implementations rely on classical controllers such as PID, which lack adaptability in dynamic traffic conditions. In this work, we propose a lightweight Reinforcement Learning (RL)-based ACC system deployed on a low-cost ESP32 microcontroller. The RL model is trained using Proximal Policy Optimization (PPO) in a custom simulation environment to learn optimal acceleration, braking, and maintaining actions. The trained model is quantized and deployed on the ESP32 using TensorFlow Lite Micro, enabling real-time decision-making with minimal hardware resources. Sensor integration is achieved through ultrasonic modules for distance measurement and a motor driver for actuation. This approach demonstrates the feasibility of embedding intelligent control in resource-constrained platforms, paving the way for affordable smart mobility solutions.

Problem statement

Conventional ACC systems struggle with:

- Delayed reaction to sudden braking or acceleration of lead vehicles.
- Poor adaptability to varying traffic densities and driver preferences.
- Limited consideration for safety overrides such as speed locking in emergencies. Therefore, the problem addressed in this work is: To design and implement an AI-driven ACC system that leverages Reinforcement Learning.



PID controllers



Mechanical problem



Reinforcement Learning

Proposed Solution

Simulation & Training

- Develop a custom traffic-following environment with inputs: ego speed, inter-vehicle distance, and relative speed.
- Train a compact PPO policy network ([32,16] layers) for safe distance maintenance.
- Export and quantize the trained model to run on embedded devices.

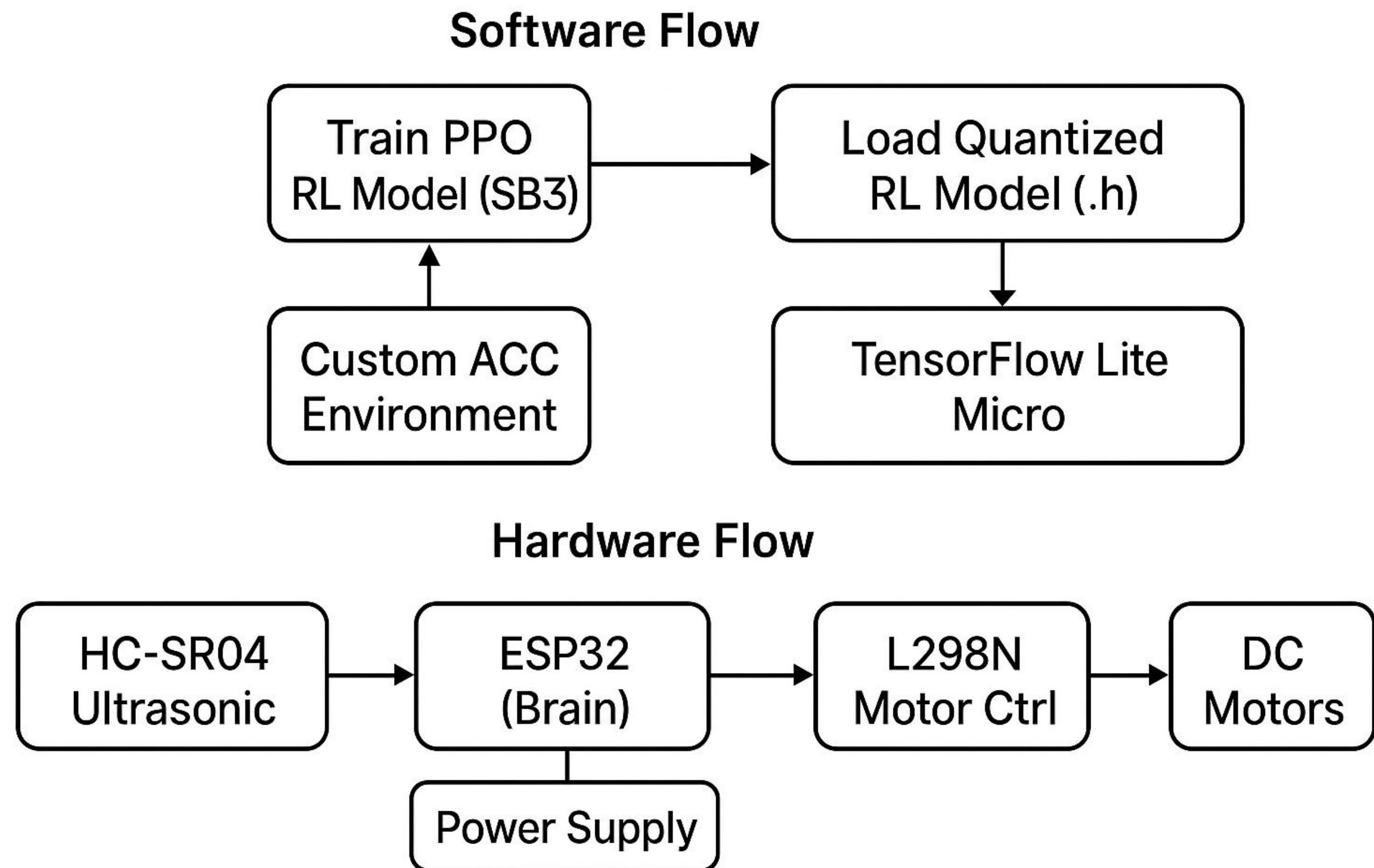
2. Deployment on ESP32

- Integrate TensorFlow Lite Micro to execute the quantized RL model.
- Use HC-SR04 ultrasonic sensor to estimate vehicle distance ahead.
- Apply RL outputs (Brake, Maintain, Accelerate) to control DC motors via L298N motor driver.

3. Control Strategy

- RL replaces PID by dynamically adapting to varying traffic situations.
- Ensures smooth acceleration, braking, and safe headway control in real-time.

Proposed System Block Diagram



Proposed Enhancements

Multi-Sensor Fusion

- Combine ultrasonic sensors with IR sensors or low-cost radar for more reliable distance and relative speed estimation.

2. Encoder Feedback

- Integrate wheel encoders or Hall sensors to estimate ego speed accurately rather than using assumptions.

3. Edge-Cloud Hybrid Training

- Offload heavy retraining to cloud or PC; periodically update ESP32 with improved models for evolving traffic patterns.

4. Energy Efficiency Optimization

- Use model pruning and quantization-aware training to further reduce computational load and power consumption.

5. Vehicle-to-Vehicle (V2V) Communication (future enhancement)

- Enable ESP32 modules in multiple vehicles to communicate via Wi-Fi or LoRa for cooperative adaptive cruise control (C-ACC).

Literature Survey

- Recent works from IEEE Xplore (2023–2025) highlight the following trends:
 - Fuel-Efficient Switching Control for Platooning Systems with Deep RL (2023) – Demonstrated that RL can improve fuel efficiency by switching between ACC and CACC modes dynamically.
 - Robust Longitudinal Control for Vehicular Platoons using Deep RL (2024/25) – Showed improved stability in vehicle spacing under disturbances and delays using RL-based controllers.
 - Safe Deep Reinforcement Learning for ACC (2024) – Used Constrained MDPs to ensure safety while optimizing speed and spacing.
 - Cooperative ACC for Electric Vehicles via Predictive Deep RL (2024)
 - Focused on energy efficiency and cooperation among electric vehicle fleets.
 - Gap Identified: While existing research proves the effectiveness of RL in ACC, there is limited integration of safety-specific features (like speed locking and proactive collision detection) into RL-based control systems, especially in mixed traffic environments

Reference Papers and their purpose

Reference Paper	Authors	<u>text</u>	Purpose	Year of publication
End-to-End Vision-Based ACC Using Deep RL	Wei et al.	The system directly processes raw visual input (camera images) to make ACC decisions, creating a fully integrated approach where the same neural network handles both object detection/distance estimation and control command generation & eliminates the need for separate perception and control modules.	2020	
Multi-Objective ACC via Deep RL	Zhang, Li Lin, Song, Huang	During the control period, it quantitatively considers three indexes: tracking accuracy, riding comfort, and fuel economy, addressing the limitation of traditional ACC systems that typically prioritize only vehicle following performance.	2022	
Model-Based RL for Advanced ACC	Yavas, Kumbasar, Ure	The research validates that model-based RL can efficiently optimize advanced ACC systems , letting autonomous vehicles learn safer and smoother car-following behaviors with less training data.	2022	
ACC Balancing Followability and Comfort via RL	Maruyama & Mouri	The paper proposes using reinforcement learning as an ACC controller that can consider various objectives to determine control inputs and balance both followability (tracking performance) and comfortability (smooth driving experience).	2022	
Safety Filtering for RL-Based ACC	Hailemichael et al.	The paper develops mathematical safety filters (control barrier functions) that prevent reinforcement learning-based adaptive cruise control systems from causing collisions while still allowing them to learn and optimize performance.	2023	
Adaptive Cruise Control via Safe Deep RL (SFRL-ACC)	Zhao et al.	The paper proposes a Safety-First Reinforcement Learning Adaptive Cruise Control (SFRL-ACC) system that prioritizes safety as a fundamental constraint during the RL policy update process, rather than merely focusing on maximizing rewards	2024	