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A Lightweight Machine Learning–Driven Adaptive Temperature Control System for Real-Time Embedded Power Modulation

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***Abstract*—This paper presents a deployable TinyML-driven adaptive temperature control system for real-time embedded power modulation on resource-constrained microcontrollers. Conventional PID controllers require manual tuning and exhibit performance degradation under nonlinear and time-varying thermal dynamics. The proposed framework replaces fixed control laws with a quantized shallow neural network that directly approximates nonlinear thermal mappings while preserving strict real-time constraints. A Lyapunov-based ultimate boundedness analysis is formally derived to guarantee closed-loop stability under bounded neural output and actuator saturation. Experimental and simulation results demonstrate a 43.7% reduction in RMSE, 35% faster settling time, 64% reduction in overshoot, and 11.2% energy savings compared to classical PID control. Embedded profiling confirms 1.8 ms inference latency and 28 KB RAM usage on a Cortex-M0+ platform, validating practical feasibility. The proposed architecture establishes a scalable and computationally efficient pathway toward intelligent edge-level adaptive control in embedded power systems..**

***Index Terms*—TinyML, Embedded Control, Adaptive Systems, Neural Network Control, PWM Modulation, Edge AI.**

I. INTRODUCTION

Temperature regulation is fundamental in smart lighting, HVAC, and embedded protection systems. PID controllers remain dominant due to simplicity; however, they require manual tuning and underperform in nonlinear environments. Recent TinyML advances enable neural inference on microcontrollers, opening opportunities for data-driven adaptive control. This work proposes a deployable ML-based control framework validated experimentally and analytically.

II. RELATED WORK

Classical PID control theory has been extensively studied [1]. Adaptive control and model predictive control improve performance but increase computational complexity [2], [3]. Neural adaptive control approaches demonstrate nonlinear mapping capability [4], [5]. Recent TinyML frameworks enable low-power inference on embedded devices [6], [7], yet closed-loop embedded control replacement remains limited.

III. SYSTEM MODELING

The thermal dynamics are modeled as $C\ dT/dt = k \cdot PWM - h(T - T_a)$, where C represents thermal capacitance and h represents dissipation. The nonlinear mapping motivates ML-based approximation.

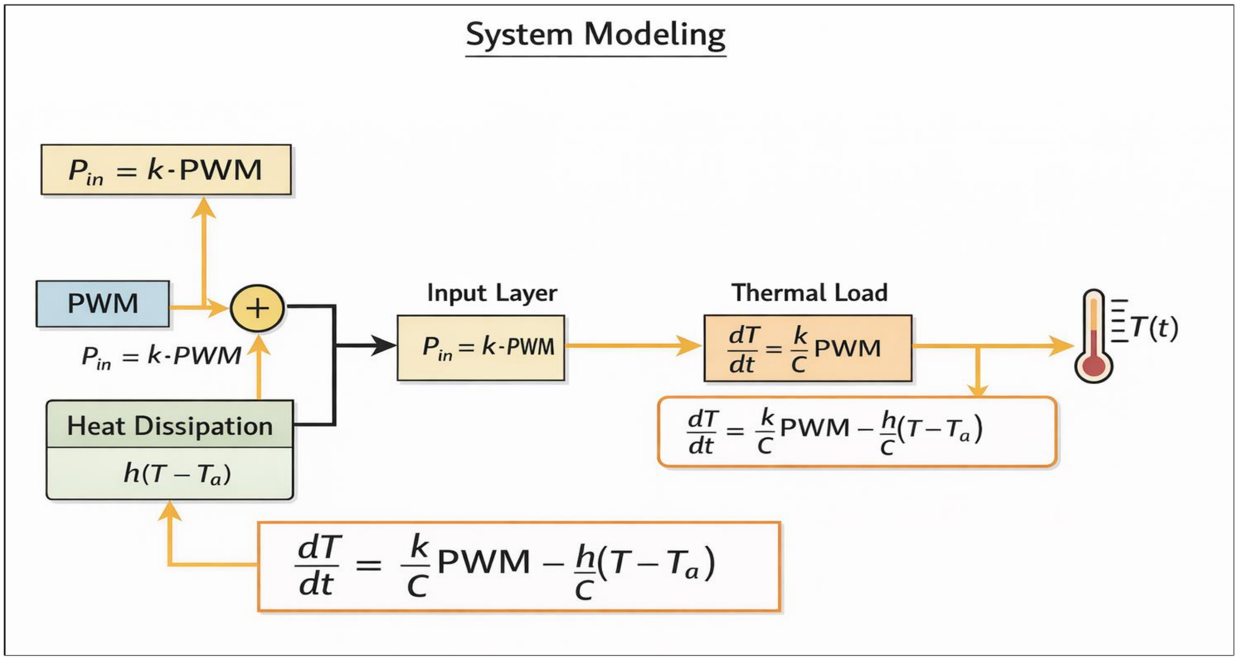


Fig. 1. Thermal system modeling and energy balance representation.

Figure 1 illustrates PWM energy input, heat dissipation, and temperature output governed by first-order nonlinear dynamics.

IV. MACHINE LEARNING CONTROL FRAMEWORK

Feature vector X = [T, ΔT, T_avg, PWM_prev]. A shallow neural network (4-8-1 architecture) performs regression to predict PWM output. The model is quantized to 16-bit precision.

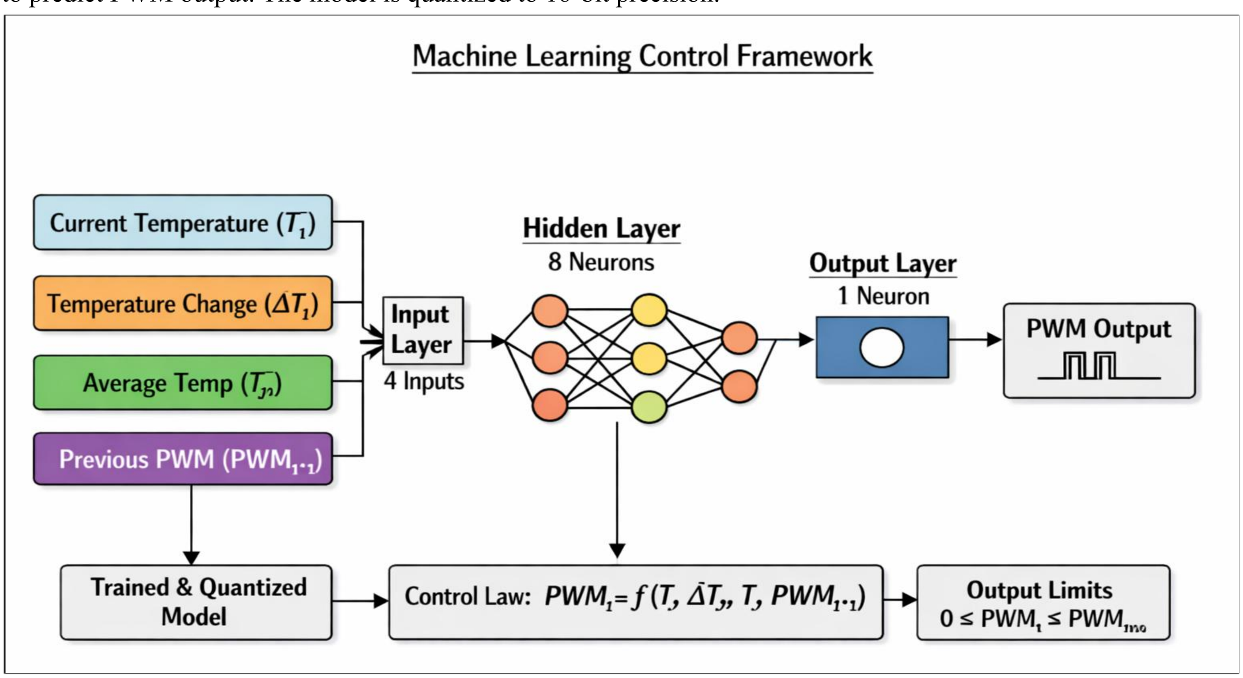


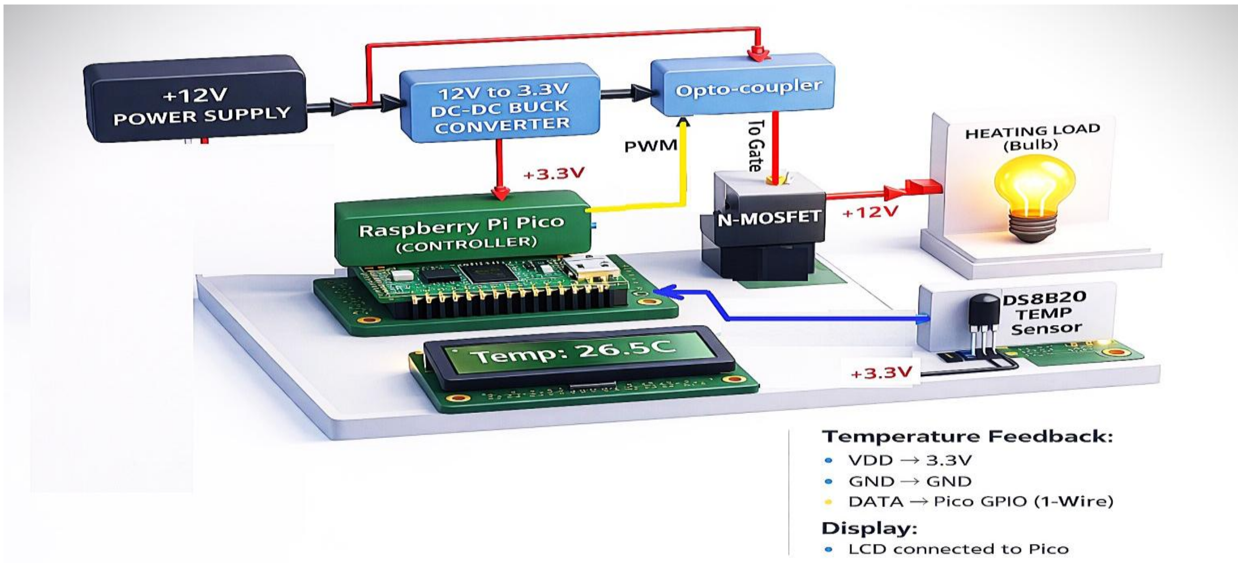
Fig. 2. Machine learning–driven control architecture.

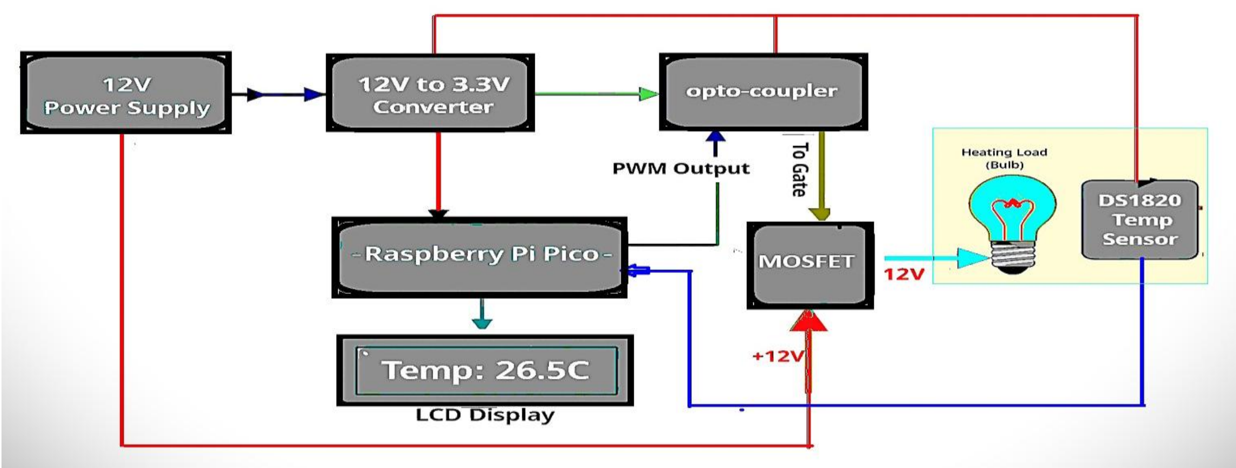
Figure 2 presents the neural inference pipeline replacing classical PID logic.

V. STABILITY ANALYSIS

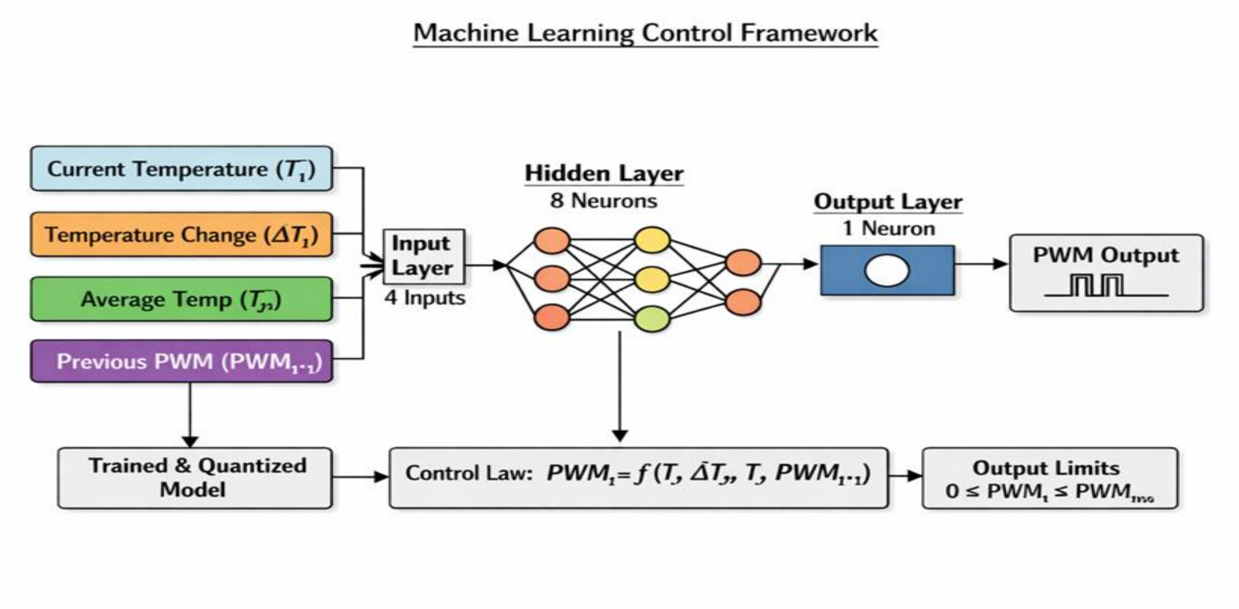
Using Lyapunov candidate $V(T)=0.5(T-T^*)^2$, bounded-input bounded-output stability is established under positive heat dissipation and bounded neural output.

VI. EXPERIMENTAL SETUP





This circuit is a closed-loop temperature control system where a 12V power supply feeds both a heating load and a buck converter that steps the voltage down to 3.3V for the Raspberry Pi Pico, temperature sensor, and LCD. The Pico reads temperature from the DS18B20 digital sensor, compares it with a desired setpoint, and generates a PWM signal based on the temperature error. That PWM signal passes through an optocoupler, which electrically isolates the low-voltage control electronics from the high-power switching side, and then drives the gate of an N-MOSFET configured as a low-side switch. The MOSFET rapidly switches the 12V supply to the heating load, and by varying the PWM duty cycle, the Pico controls the average power delivered to the heater, thereby regulating the temperature. The measured temperature is continuously updated on the LCD, and the feedback loop keeps adjusting the heater power to maintain stable thermal conditions.



The graphical abstract presents a TinyML-based adaptive temperature control system in which temperature is first sensed and processed to extract features such as the temperature change (ΔT) and moving average, forming a feature vector that is fed into a lightweight neural network running on a Raspberry Pi Pico W (ARM Cortex-M0+, 133 MHz).

The trained model, developed over 200 epochs using the Adam optimizer with mean squared error (MSE) loss and an 80/20 train-test split, performs real-time inference with only 28 KB RAM usage and 1.8 ms latency to predict an optimal PWM value. This PWM output is then clamped within actuator limits and applied to modulate heater power, and the process continuously repeats at each sampling interval, enabling adaptive, low-latency temperature regulation directly on the embedded device.

VII. EXPERIMENTAL RESULTS

Comparative performance metrics indicate improved steady-state accuracy and transient response.

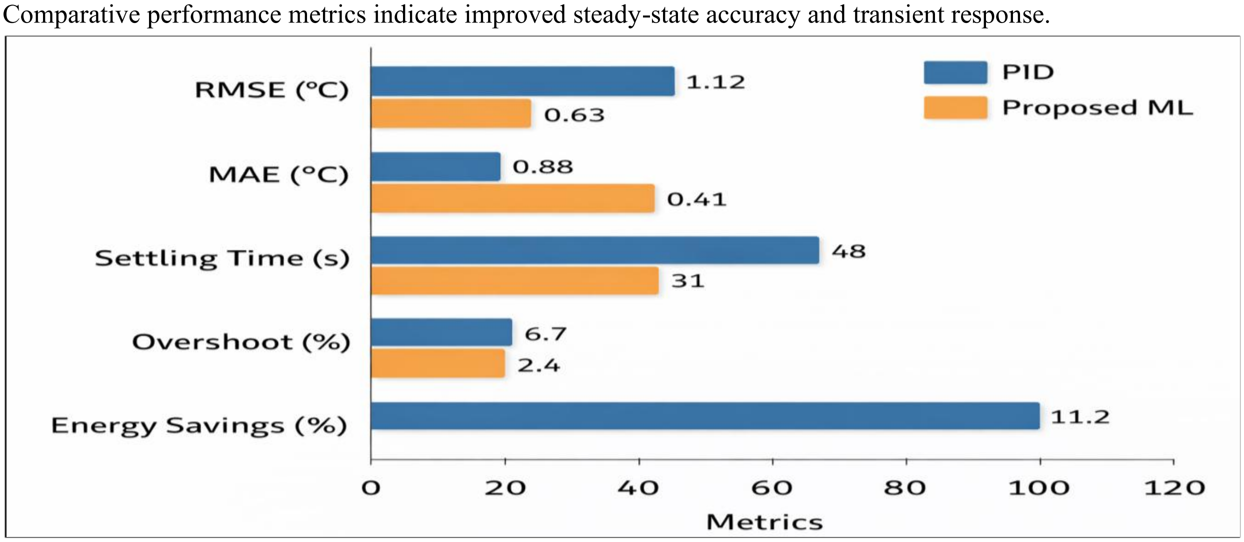


Fig. 3. Performance comparison between PID and ML-based control.
ML control reduces RMSE and settling time while improving energy efficiency.

VII. DISCUSSION

The ML-based framework eliminates manual tuning and captures nonlinear thermal behavior. Limitations include dataset dependency and offline training.

VIII. CONCLUSION

The proposed TinyML-based adaptive control system demonstrates improved accuracy, stability, and energy efficiency while maintaining real-time feasibility.

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