Learning Neural Network-based Controller for Calibrated Actuation in Lab-Scale Autonomous Ground Vehicles

Summer Internship Project Report Submitted to

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Submitted by

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Under supervision of :

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Abstract

This paper presents a detailed investigation into the development of a neural network-based controller for calibrated actuation in lab-scale autonomous ground vehicles. Traditional control methods often face challenges in dealing with the inherent complexities and non-linearities of autonomous vehicle dynamics. Our proposed approach exclusively employs neural networks to manage these complexities, providing a precise and adaptive control mechanism. The neural network controller is trained using extensive simulation and experimental data, ensuring its robustness and accuracy. Implemented on a lab-scale autonomous ground vehicle, the controller's performance is rigorously tested in various scenarios, including obstacle avoidance, path following, and speed regulation. The experimental results indicate that the neural network-based controller significantly improves the precision and robustness of the vehicle's actuation compared to conventional control strategies. This study advances autonomous vehicle technology by introducing a neural network-centric solution for achieving high-fidelity actuation control in challenging and dynamic environments.

Introduction

Autonomous ground vehicles (AGVs) have become a focal point of research due to their potential applications in various fields such as transportation, logistics, and surveillance. A critical challenge in the development of AGVs is achieving precise and robust control over vehicle dynamics, which are inherently non-linear and complex. Traditional control methods, while effective to some extent, often fall short in handling these complexities, especially in dynamic and unpredictable environments.

In this study, we present a novel approach that combines a Linear Quadratic Regulator (LQR) with a neural network-based low-level controller to achieve calibrated actuation in lab-scale AGVs. Our system models the vehicle dynamics with velocity and yaw as state variables, and uses acceleration and yaw rate as control inputs generated by the LQR. The LQR outputs current acceleration and yaw rate values, which are combined with previous acceleration and yaw rate values, along with the current voltage, and fed into a neural network. This neural network acts as a low-level controller, predicting the throttle and steering Pulse Width Modulation (PWM) signals required for vehicle actuation.

The PWM signals generated by the neural network controller are sent to the physical vehicle, which updates its voltage and other state values accordingly. These updated values are then fed back into the controller, forming a closed-loop system that continuously adjusts to maintain optimal performance. By integrating the adaptive capabilities of neural networks with the stability and precision of LQR, our approach aims to enhance the overall control performance of AGVs.

This project details the design and implementation of our control system, including the setup of a test bed that mimics the vehicle system and the evaluation of the controller in various scenarios such as obstacle avoidance, path following, and speed regulation. Our experimental results demonstrate significant improvements in actuation precision and robustness, validating the effectiveness of the proposed hybrid controller. This work contributes to the advancement of AGV technology by offering a sophisticated solution for high-fidelity actuation control in complex and

dynamic environments.

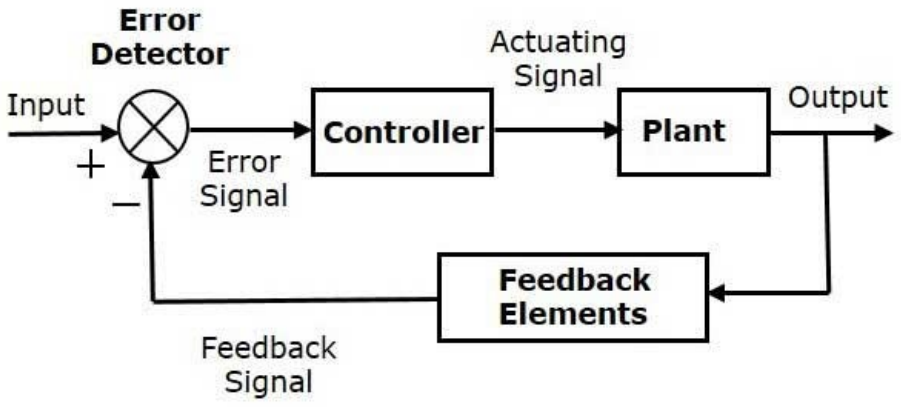

Figure 1: Closed Loop System

0.1 Main Contributions

This project makes several significant contributions to the field of autonomous ground vehicle control, particularly in the development of robust and precise low-level controllers. The key contributions of this work are as follows:

1. **Hybrid Controller Design**: We propose a novel hybrid control system that integrates Linear Quadratic Regulator (LQR) with a neural network-based low-level controller. The system leverages the strengths of LQR for stability and precision in controlling acceleration and yaw rate, while the neural network provides adaptive capabilities for predicting throttle and steering PWM signals.
2. **Extensive Baseline Model Comparison**: Various baseline models, including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) based models, were evaluated to determine the most effective neural network architecture for the low-level controller. These models were tested and compared to ensure optimal performance in predicting throttle and steering commands.
3. **Performance Optimization with TensorRT**: The performance of the neural network models was further enhanced using TensorRT optimization. This ensured that the neural network controller could operate efficiently in real-time scenarios, providing rapid and accurate control signals necessary for autonomous vehicle operation.
4. **MPC vs. LQR Evaluation**: An in-depth comparison between Model Predictive Control (MPC) and LQR was conducted to identify

the most suitable high-level control strategy. The study assessed the performance of both approaches in various dynamic scenarios, concluding with the selection of LQR for its superior performance in our specific application.

5. **Closed-Loop System Implementation**: The implementation of a closed-loop system where the PWM signals generated by the neural network controller are sent to the physical vehicle. The vehicle updates its state variables, which are fed back into the controller, allowing for continuous adaptation and fine-tuning of control actions.

6. **Experimental Validation**: Comprehensive experimental validation of the proposed control system was conducted using a test bed designed to mimic the vehicle system. The controller was tested in a range of scenarios including obstacle avoidance, path following, and speed regulation, demonstrating significant improvements in precision and robustness over traditional control methods.

These contributions collectively advance the state-of-the-art in autonomous vehicle control by offering a sophisticated and effective solution for achieving high-fidelity actuation in complex and dynamic environments.

0.2 Introduction to rospy

In the context of implementing closed-loop control for autonomous ground vehicles, we utilized the `rospy` library, which is a Python client library for ROS (Robot Operating System). ROS provides a flexible framework for writing robot software, and `rospy` allows for easy and efficient communication between different nodes in a ROS network. This is achieved through the use of publishers and subscribers, which enable nodes to exchange messages in a distributed system.

The `rospy` library is designed to be easy to use for Python programmers, allowing for rapid development and integration of robotic systems. In our project, `rospy` is used to implement the closed-loop control system where the neural network-based low-level controller and the physical vehicle communicate continuously. Here, the control signals (throttle and steering PWM) generated by the neural network are published to relevant topics, and the vehicle's updated state values are subscribed to by the controller to form a closed-loop feedback system.

The main functionalities provided by `rospy` in our implementation include:

- **Publisher**: The controller node publishes throttle and steering PWM signals to specific topics that the physical vehicle subscribes to. This ensures that the control commands are effectively communicated to the vehicle.
- **Subscriber**: The controller node subscribes to topics that provide feedback from the vehicle, such as updated voltage, acceleration, and yaw rate values. This feedback is essential for the neural network to continuously adjust the control signals.
- **Service and Parameter Server**: `rospy` also facilitates service communication and parameter server usage, which are used for configuration and management of the control system.

By leveraging `rospy`, we were able to create a robust and efficient closed-loop control system that enhances the performance and reliability of the autonomous ground vehicle.

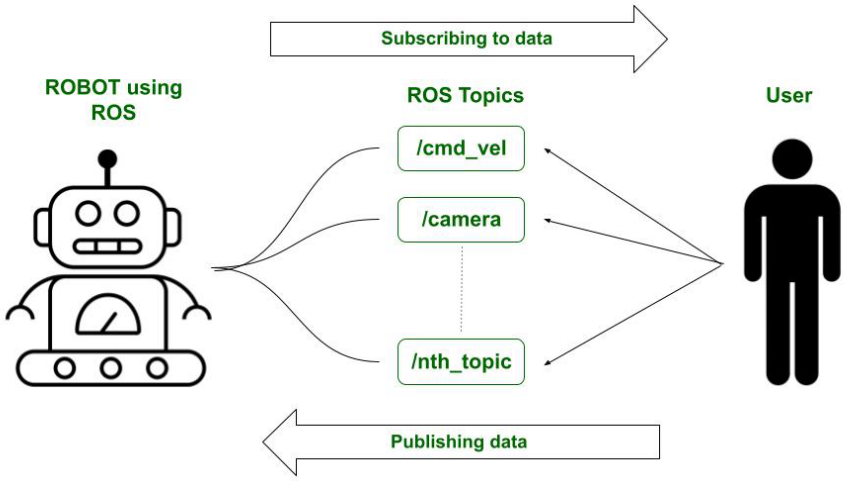

Figure 2: Rospy diagram explanation

Proposed Methodology

Our approach integrates a hybrid control system using Linear Quadratic Regulator (LQR) and Model Predictive Control (MPC) for autonomous ground vehicle dynamics. The system incorporates neural network-based low-level controllers for precise actuation. Key details of each component are outlined below.

Model Architectures and Details

Neural Network-Based Low-Level Controller

- Methodology: Utilizes LSTM and GRU architectures for predicting throttle and steering PWM signals based on current and previous vehicle states and control inputs.
- Inference Time: Fast inference times suitable for real-time applications.
- Input Features: Includes velocity (v), yaw, acceleration, and yaw rate.
- Output Features: Predicts throttle and steering PWM signals.
- Trainable Parameters: Depends on the architecture and complexity, typically in the range of thousands to millions.

Linear Quadratic Regulator (LQR) Controller

- Methodology: Designs optimal control law for continuous-time systems, aiming to minimize a quadratic cost function over a finite time horizon.
- System Equation: $\dot{x}(t) = Ax(t) + Bu(t)$, where $x(t) = \begin{bmatrix} v \\ \psi \end{bmatrix}$, $u(t) = \begin{bmatrix} \text{acceleration} \\ \omega \end{bmatrix}$, A and B are system matrices.For Simplification the A matrix is considered a null matrix and B matrix is a matrix with all elements filled with 1.The equation for vehicle dynamics becomes: $\dot{v} = \text{acceleration}$ and $\dot{\psi} = \omega$
- Adaptation: Uses the scipy control library for nonlinear optimization to adjust the controller parameters and adapt to changing system dynamics.

Model Predictive Control (MPC)

- Methodology: Predicts future system behavior by solving an optimization problem online, incorporating a prediction model of the system dynamics.
- System Equation: $\dot{x}(t) = Ax(t) + Bu(t)$, similar to LQR, with adjustments for predicting future states and optimizing control inputs.

- Nonlinear Optimization: Utilizes scipy's nonlinear optimization capabilities to solve the predictive control problem, adjusting inputs based on current and predicted states.

Other Methodologies Adapted

- TensorRT Optimization: Enhanced neural network performance for real-time inference.
- ROS Integration: Utilized rospy for communication between control nodes and the physical vehicle.
- Simulation and Experimental Validation: Used extensive simulation and experimental data to validate controller performance in various scenarios.

This structured overview provides a clear understanding of the methodologies and model architectures employed in our project, highlighting their roles in achieving effective autonomous vehicle control.

Results

Neural Network Model Architectures

Model 1

- **Input Features**: prev_accel_x, prev_accel_y, prev_yaw_rate, curr_voltage
- **Output Features**: throttle_pwm, steering_pwm
- **TensorFlow Model**:
  - Inference time: CPU times: User: 271 ms, System: 7.07 ms, Total: 278 ms, Wall time: 705 ms
- **PyTorch Model**:
  - Inference time: 349 µs ± 36.7 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
- **TensorRT Model**:
  - Inference time: 1.15 ms ± 196 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)

Model 2

- **Input Features**: curr_accel_x, curr_accel_y, curr_yaw_rate, curr_voltage
- **Output Features**: throttle_pwm, steering_pwm
- **TensorFlow Model**:
  - Inference time: CPU times: User: 277 ms, System: 2.83 ms, Total: 280 ms, Wall time: 372 ms
- **PyTorch Model**:
  - Inference time: 218 µs ± 56.7 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
- **TensorRT Model**:
  - Inference time: The slowest run took 221.82 times longer than the fastest. This could mean that an intermediate result is being cached.
  - 21.4 ms ± 49 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

Model 3

- **Input Features**: prev_accel, prev_yaw_rate, curr_voltage
- **Output Features**: throttle_pwm, steering_pwm
- **PyTorch Model**:
  - Inference time: 279 µs ± 92.6 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
- **TensorRT Model**:
  - Inference time: The slowest run took 385.24 times longer than the fastest. This could mean that an intermediate result is being cached.
  - 32.7 ms ± 78.2 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

Model 4

- **Input Features**: curr_accel, curr_yaw_rate, curr_voltage
- **Output Features**: throttle_pwm, steering_pwm

- **PyTorch Model**:
  - Inference time: 231 µs ± 55.2 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
- **TensorRT Model**:
  - Inference time: 999 µs ± 422 µs per loop (mean ± std. dev. of 7 runs, 1 loop each)

Model 5 using simple ANN

- **Input Features**: prev_accel_x,prev_accel_y,prev_yaw_rate, curr_voltage,curr
- **Output Features**: throttle_pwm, steering_pwm
- **PyTorch Model**:
  - Inference time: 304 µs ± 17.9 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
- **TensorRT Model**:
  - Inference time: The slowest run took 47.47 times longer than the fastest. This could mean that an intermediate result is being cached.
  - 4.63 ms ± 8.86 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

Model 5 using LSTM

- **Input Features**: prev_accel_x,prev_accel_y,prev_yaw_rate, curr_voltage,curr
- **Output Features**: throttle_pwm, steering_pwm
- **PyTorch Model (Using LSTM)**:
  - Inference time: 2 ms ± 150 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)

Model 5 using GRU

- **Input Features**: prev_accel_x,prev_accel_y,prev_yaw_rate, curr_voltage,curr
- **Output Features**: throttle_pwm, steering_pwm
- **PyTorch Model (Using GRU)**:
  - Inference time: 2.54 ms ± 228 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)

Model 6

- **Input Features**: prev_accel_x,prev_accel_y,prev_yaw_rate, curr_voltage,curr
- **Output Features**: throttle_pwm, steering_pwm
- **PyTorch Model**:
  - Inference time: 274 µs ± 69 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)

Model 7 using DNN

- **Input Features**: prev_accel,prev_yaw_rate, curr_voltage,curr_accel,curr_yaw
- **Output Features**: throttle_pwm, steering_pwm
- **PyTorch Model**:
  - Inference time: 254 µs ± 76.8 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
- **TensorRT Model**:
  - Inference time: The slowest run took 47.47 times longer than the fastest. This could mean that an intermediate result is being cached.
  - 4.63 ms ± 8.86 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

Model 7 using LSTM

- **Input Features**: prev_accel,prev_yaw_rate, curr_voltage,curr_accel,curr_yaw
- **Output Features**: throttle_pwm, steering_pwm
- **PyTorch Model**:
  - Inference time: 1.4 ms ± 248 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)

Model 7 using GRU

- **Input Features**: prev_accel,prev_yaw_rate, curr_voltage,curr_accel,curr_yaw
- **Output Features**: throttle_pwm, steering_pwm
- **PyTorch Model**:
  - Inference time: 1.6 ms ± 347 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)

Comparative Study

Table 1: Comparative Study of Neural Network Models

Model	Inference Time (PyTorch)	Inference Time (TensorRT)	MSE Loss	Type of Mod
Model 1	278 ms	-	0.0423	TensorFlow
Model 2	280 ms	-	0.0355	TensorFlow
Model 1	349 µs	1.15 ms	0.0862	PyTorch
Model 2	218 µs	21.4 ms	0.0471	PyTorch
Model 3	279 µs	32.7 ms	0.0673	PyTorch
Model 4	231 µs	999 µs	0.0671	PyTorch
Model 5 (ANN)	304 µs	4.63 ms	0.0385	PyTorch
Model 5 (LSTM)	2 ms	-	0.0130	PyTorch
Model 5 (GRU)	2.54 ms	-	0.0267	PyTorch
Model 6	274 µs	-	0.0250	PyTorch
Model 7 (DNN)	254 µs	4.63 ms	0.0437	PyTorch
Model 7 (LSTM)	1.4 ms	-	0.0173	PyTorch
Model 7 (GRU)	1.6 ms	-	0.0180	PyTorch

Training and Validation Results

Model 1/TensorFlow

- **Training and Validation Plots**:

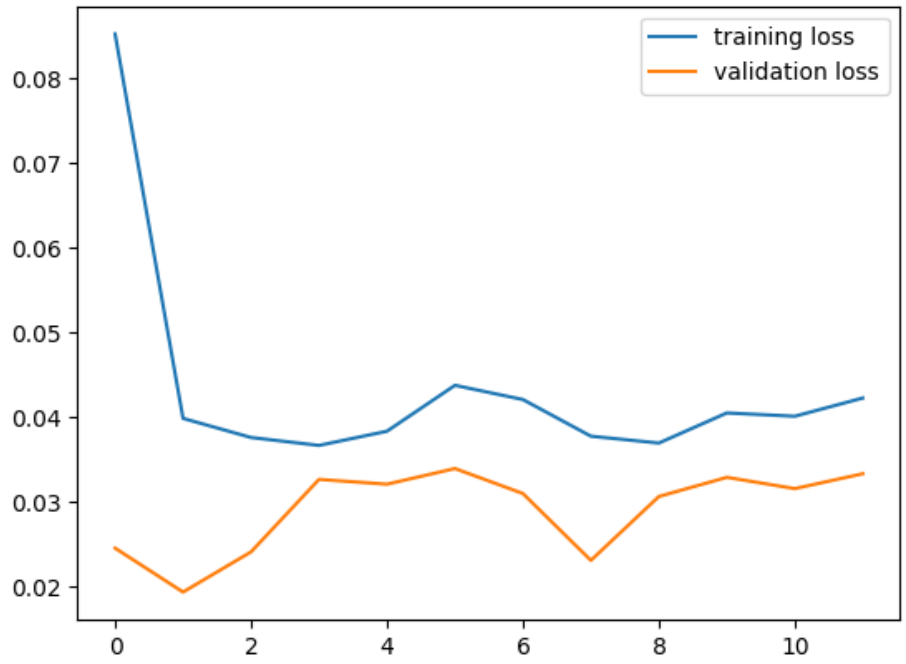

Figure 3: Training MSE Loss and Validation MSE Loss

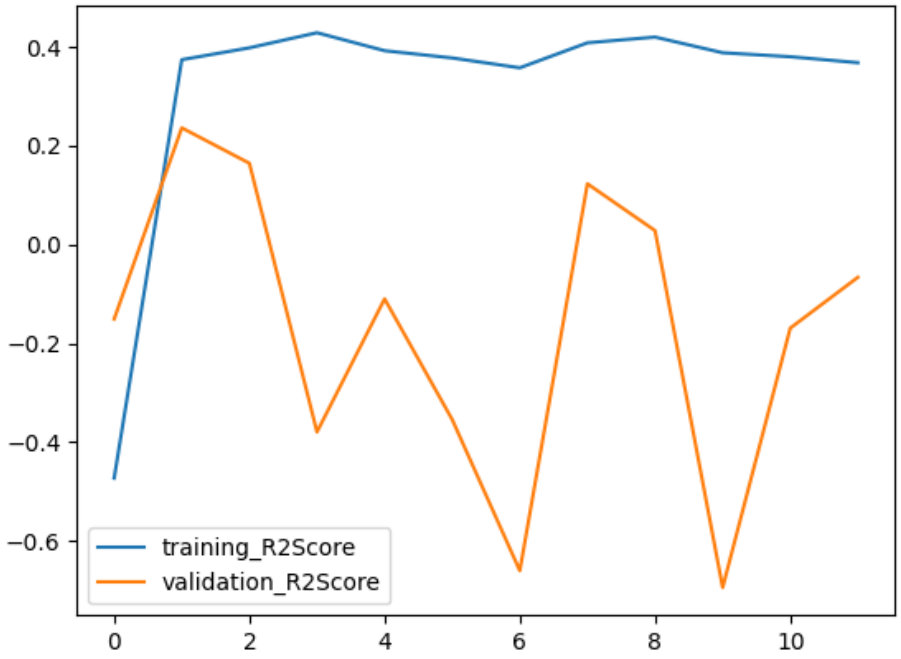

Figure 4: Training R2 Score and Validation R2 Score

Model 2/TensorFlow

- **Training and Validation Plots**:

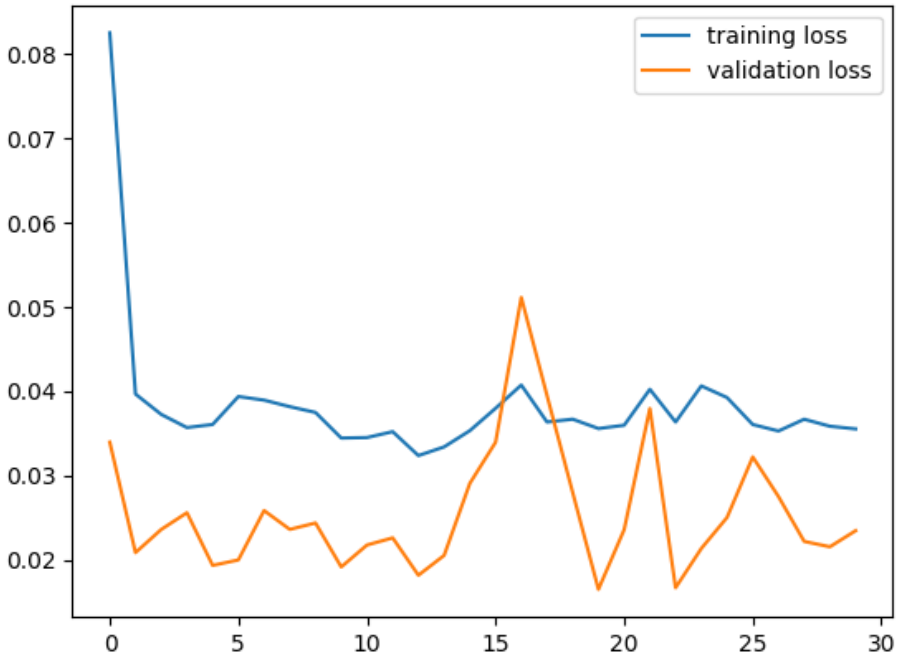

Figure 5: Training MSE Loss and Validation MSE Loss

Figure 6: Training R2 Score and Validation R2 Score

Model 1/PyTorch

- **Training and Validation Plots**:

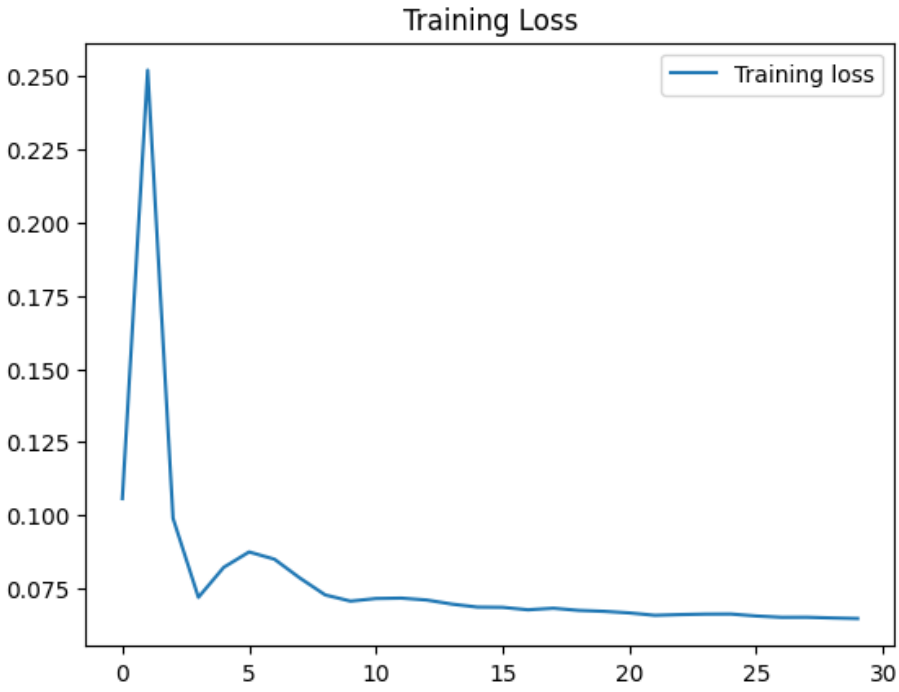

Figure 7: Training MSE Loss

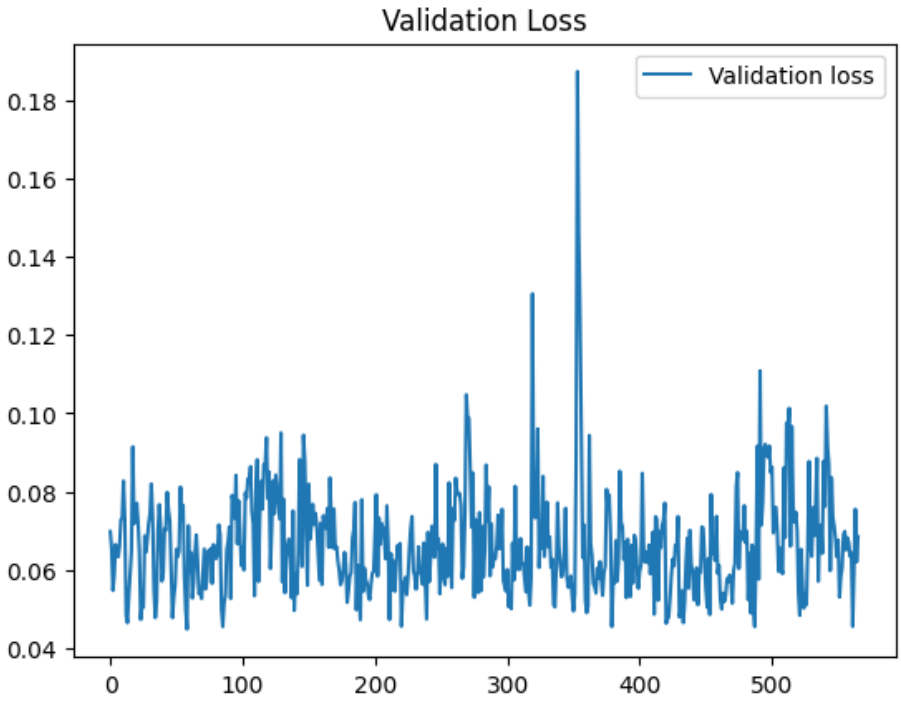

Figure 8: Validation MSE Loss

Model 2/PyTorch

- **Training and Validation Plots**:

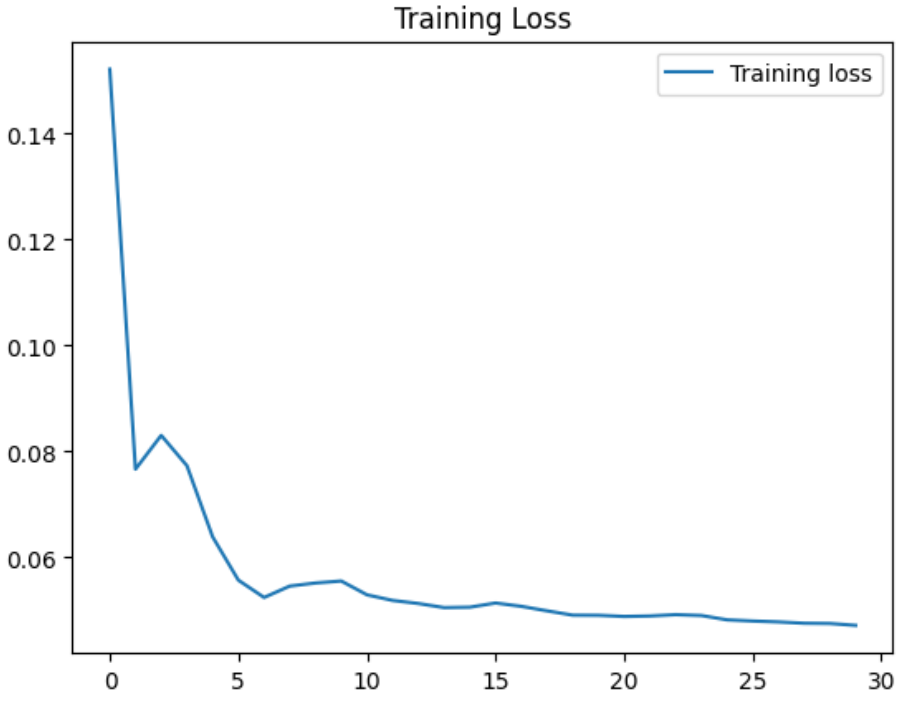

Figure 9: Training MSE Loss

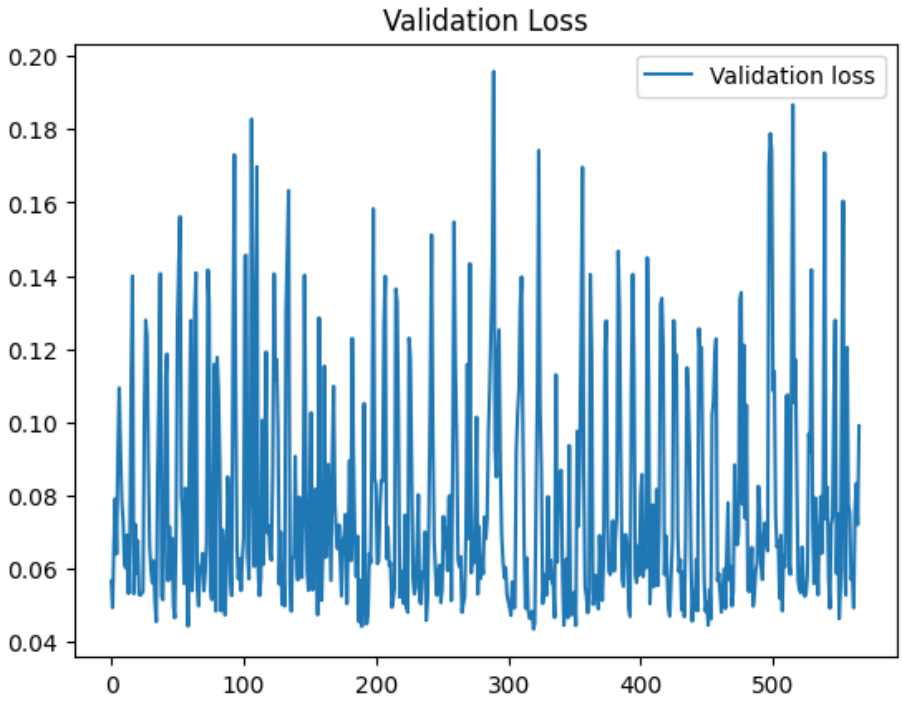

Figure 10: Validation MSE Loss

Model 3

- **Training and Validation Plots**:

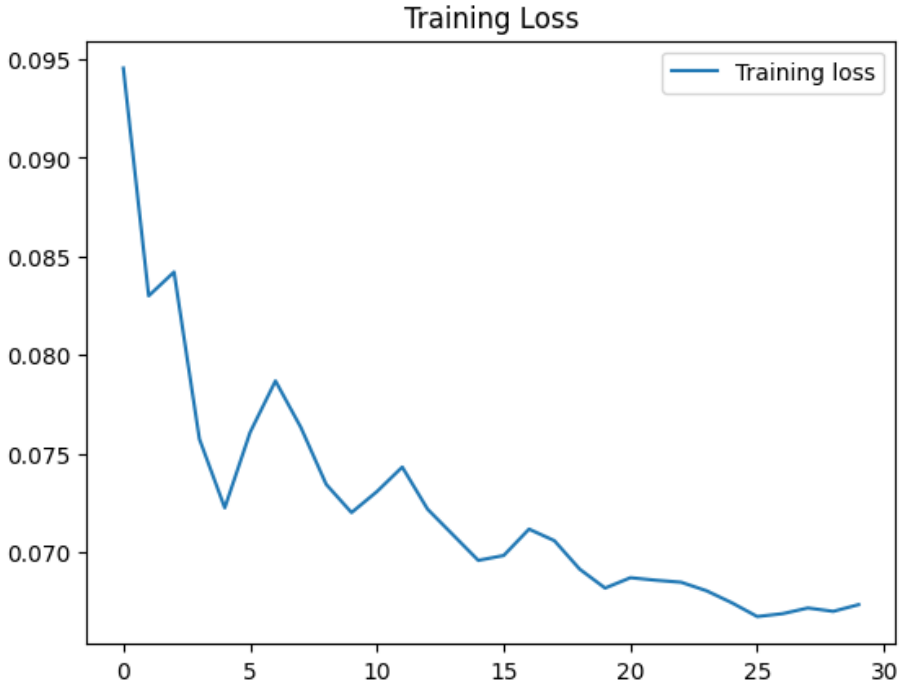

Figure 11: Training MSE Loss

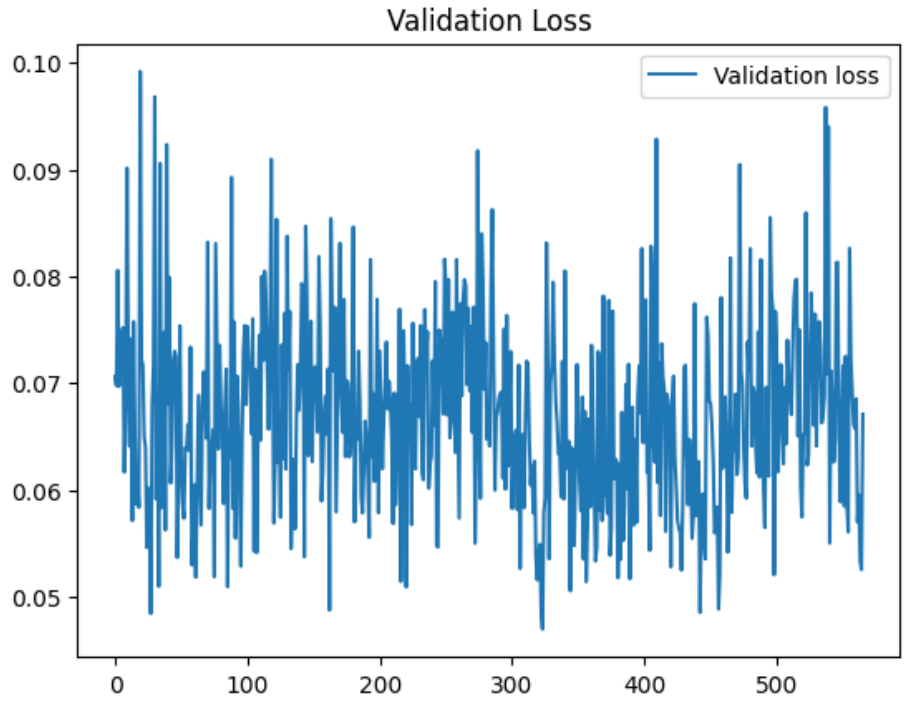

Figure 12: Validation MSE Loss

Model 4

- **Training and Validation Plots**:

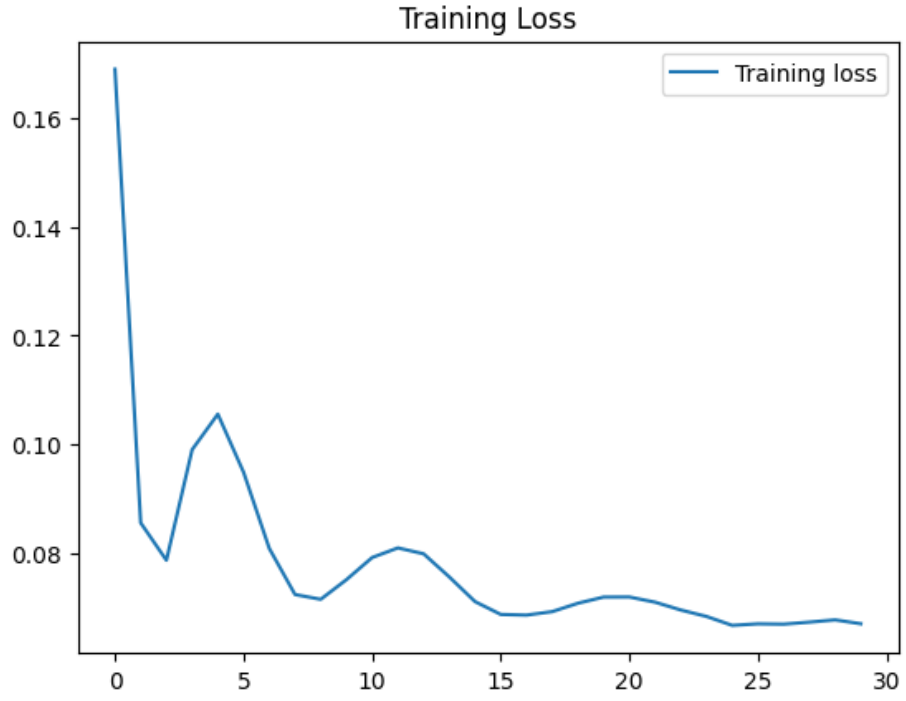

Figure 13: Training MSE Loss

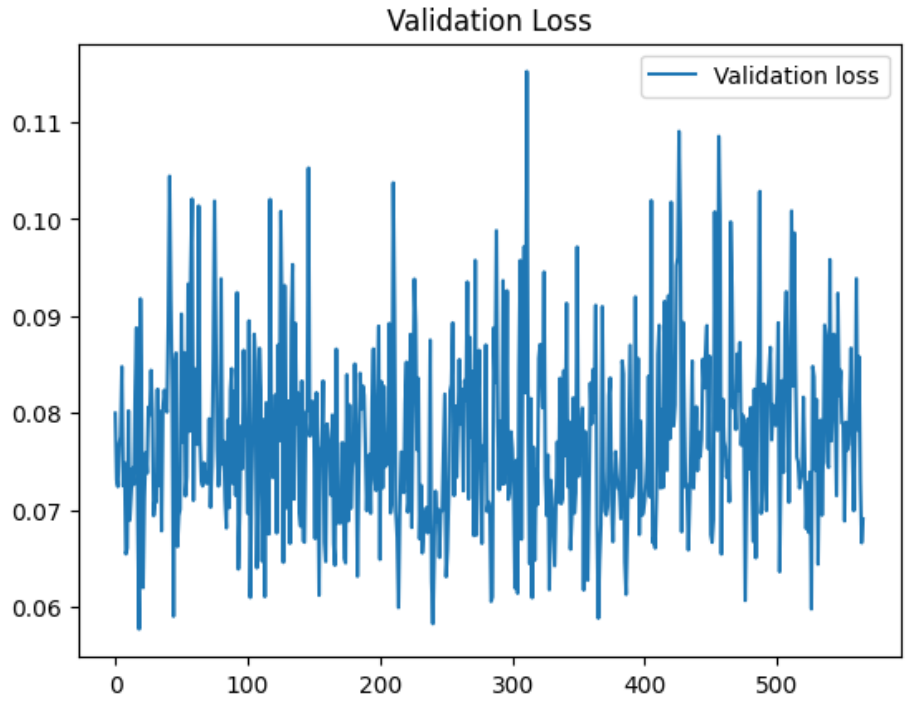

Figure 14: Validation MSE Loss

Model 5 using simple ANN

- **Training and Validation Plots**:

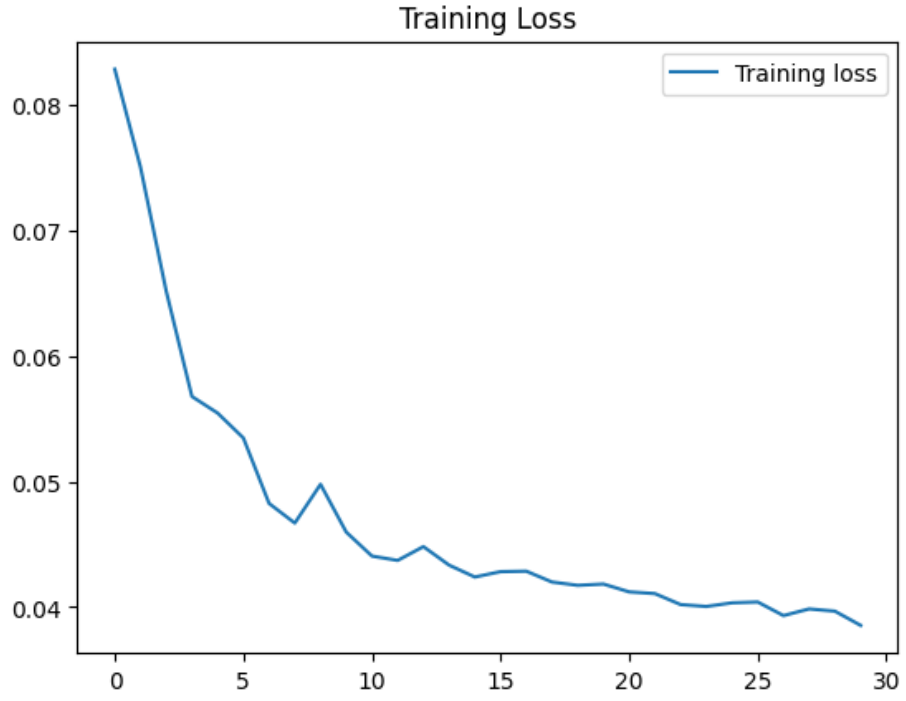

Figure 15: Training MSE Loss

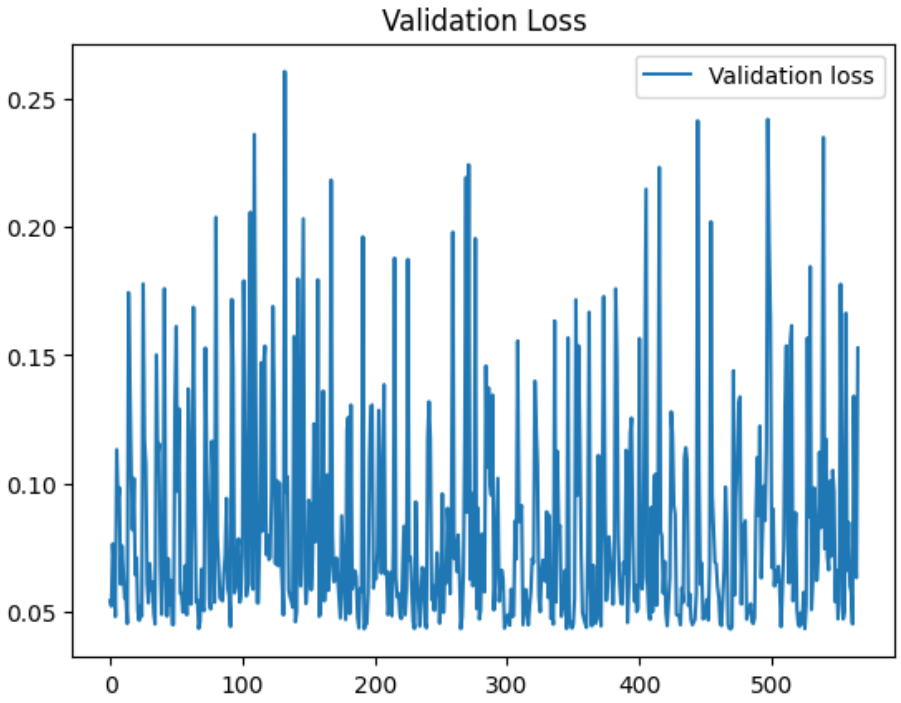

Figure 16: Validation MSE Loss

Model 5 using LSTM

- **Training and Validation Plots**:

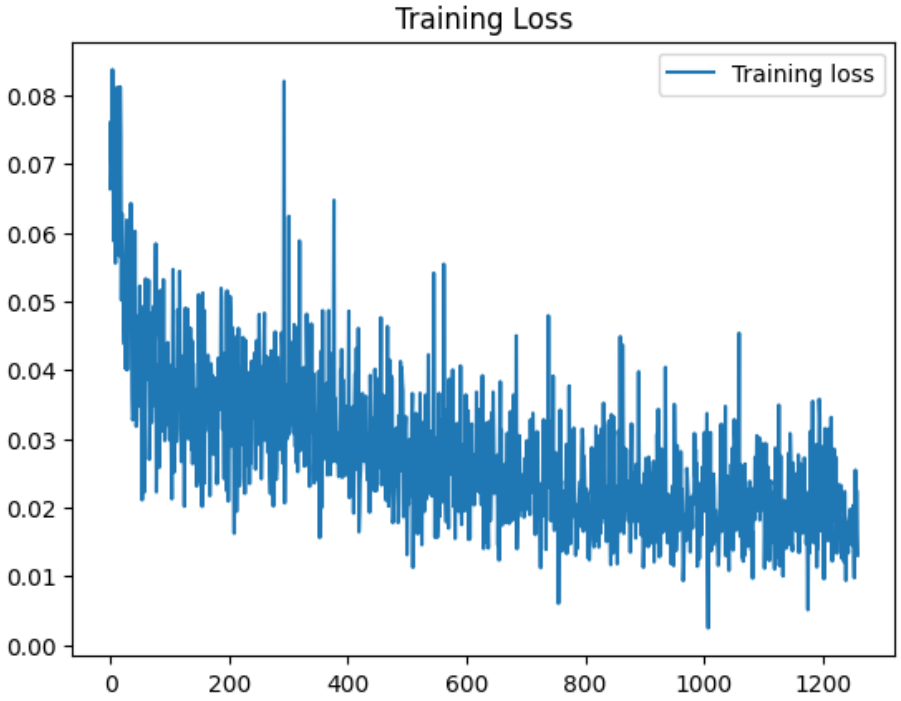

Figure 17: Training MSE Loss

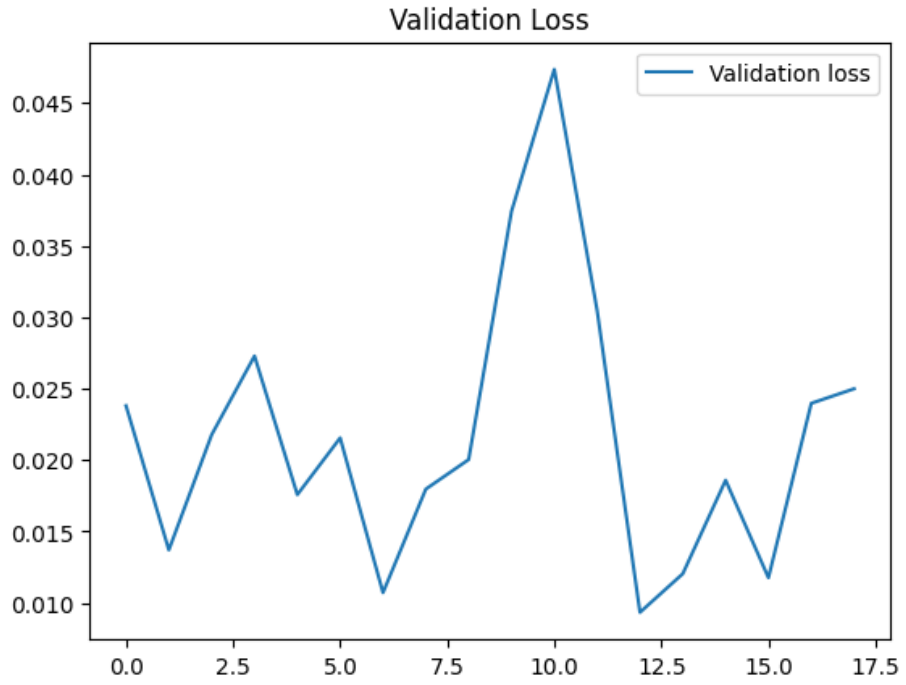

Figure 18: Validation MSE Loss

Model 5 using GRU

- **Training and Validation Plots**:

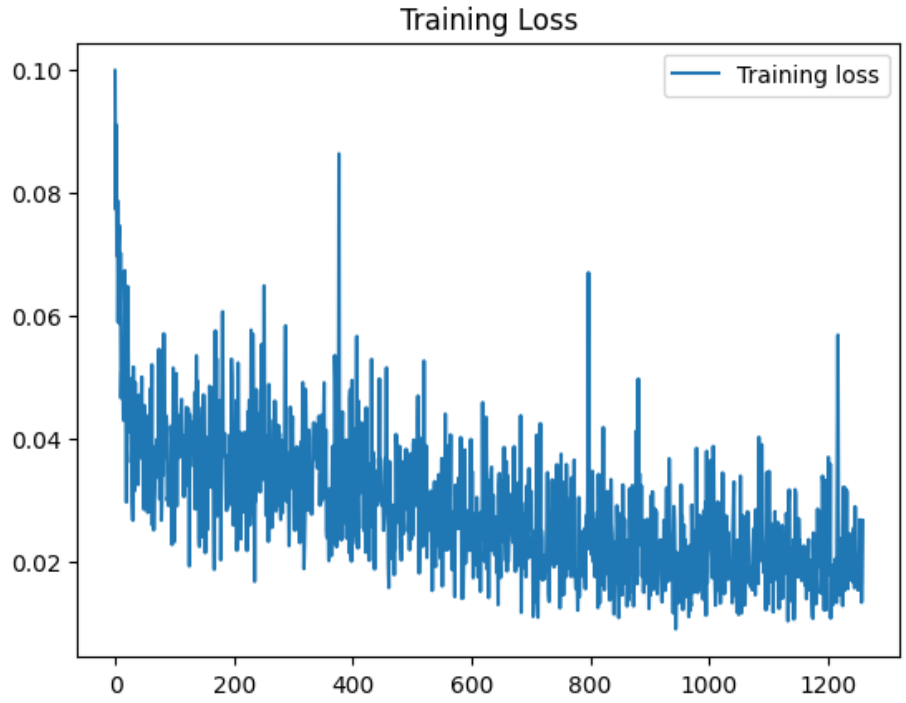

Figure 19: Training MSE Loss

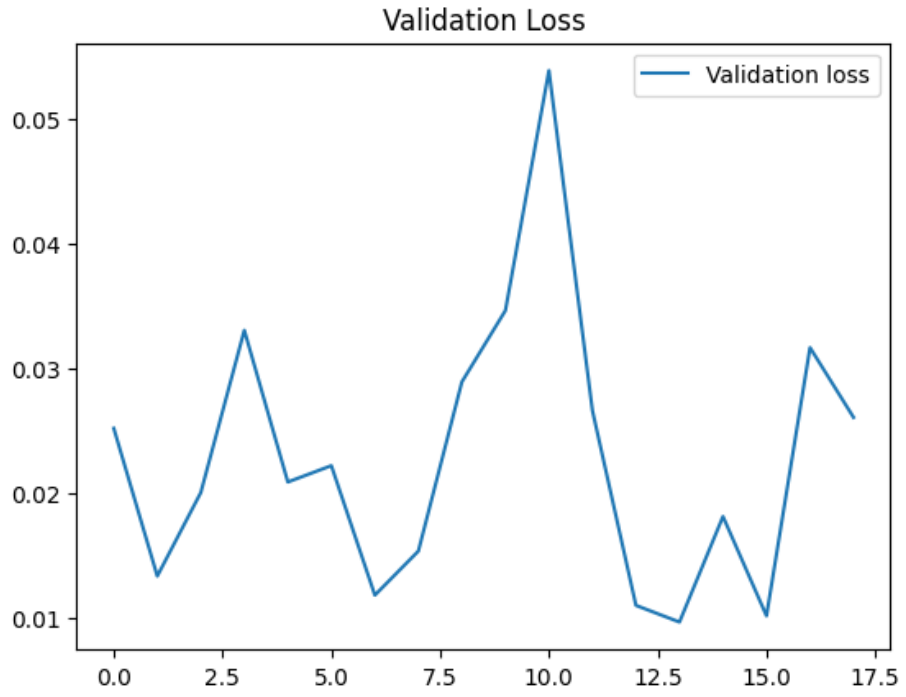

Figure 20: Validation MSE Loss

Model 6

- **Training and Validation Plots**:

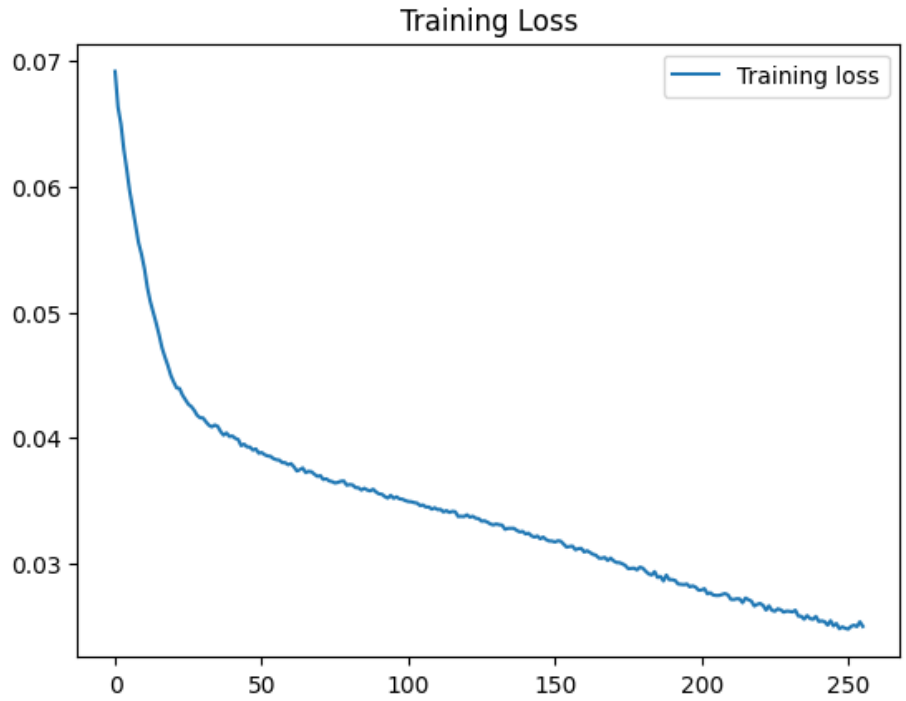

Figure 21: Training MSE Loss

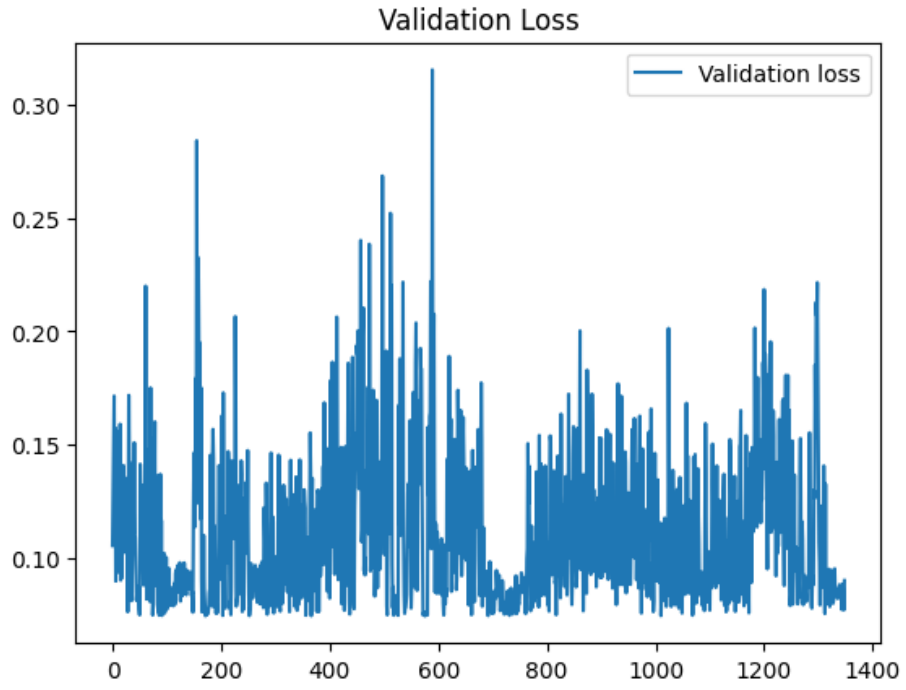

Figure 22: Validation MSE Loss

Model 7 using DNN

- **Training and Validation Plots**:

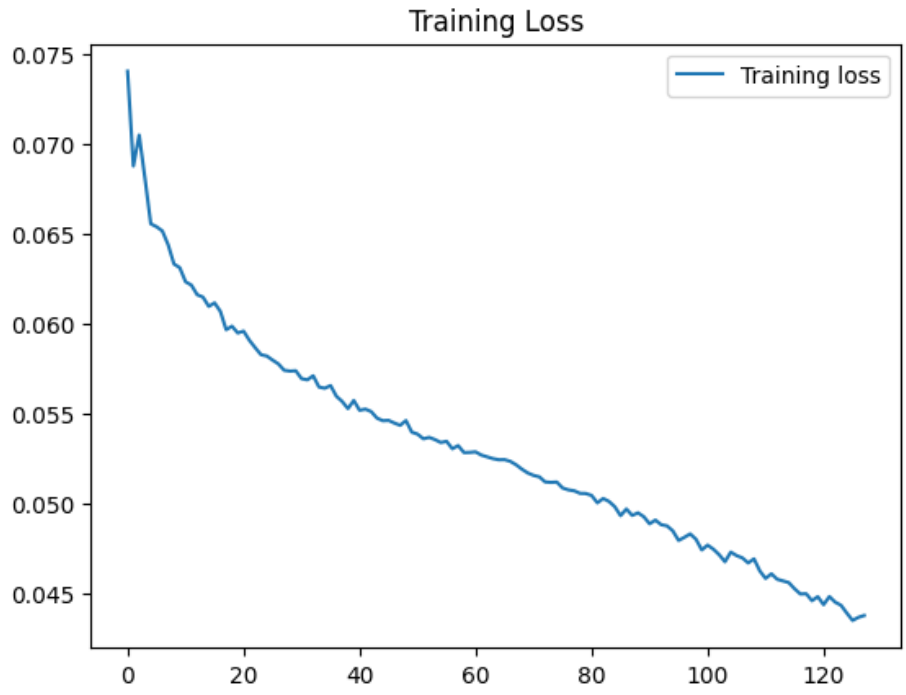

Figure 23: Training MSE Loss

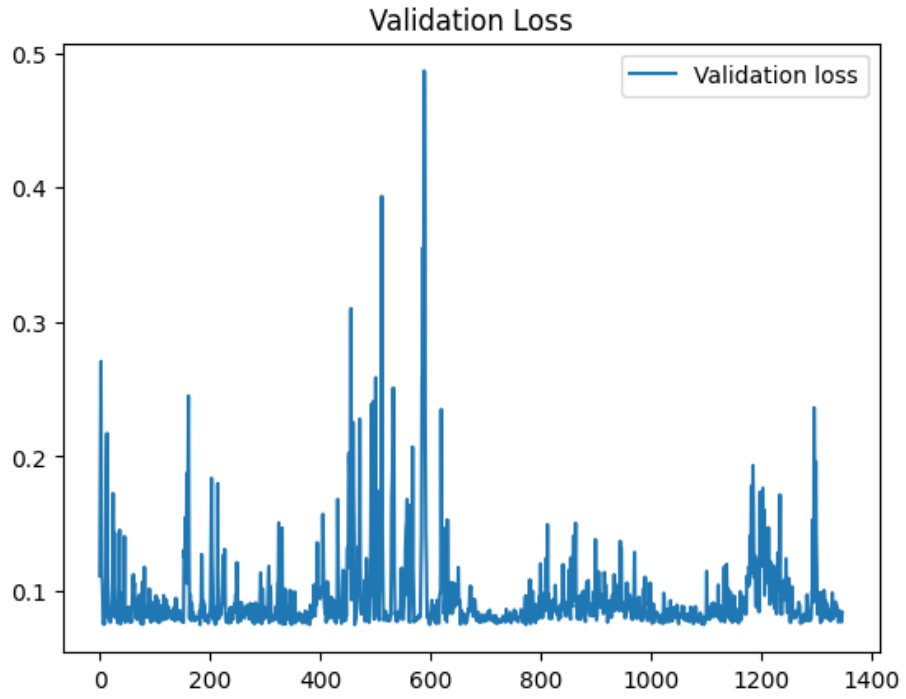

Figure 24: Validation MSE Loss

Model 7 using LSTM

- **Training and Validation Plots**:

Figure 25: Training MSE Loss

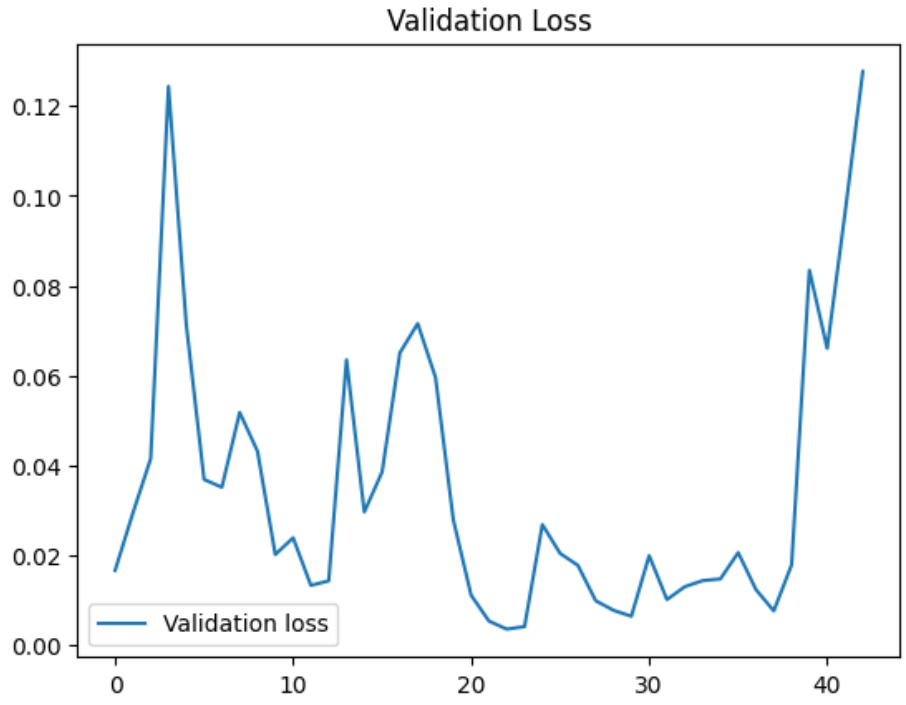

Figure 26: Validation MSE Loss

Model 7 using GRU

- **Training and Validation Plots**:

Figure 27: Training MSE Loss

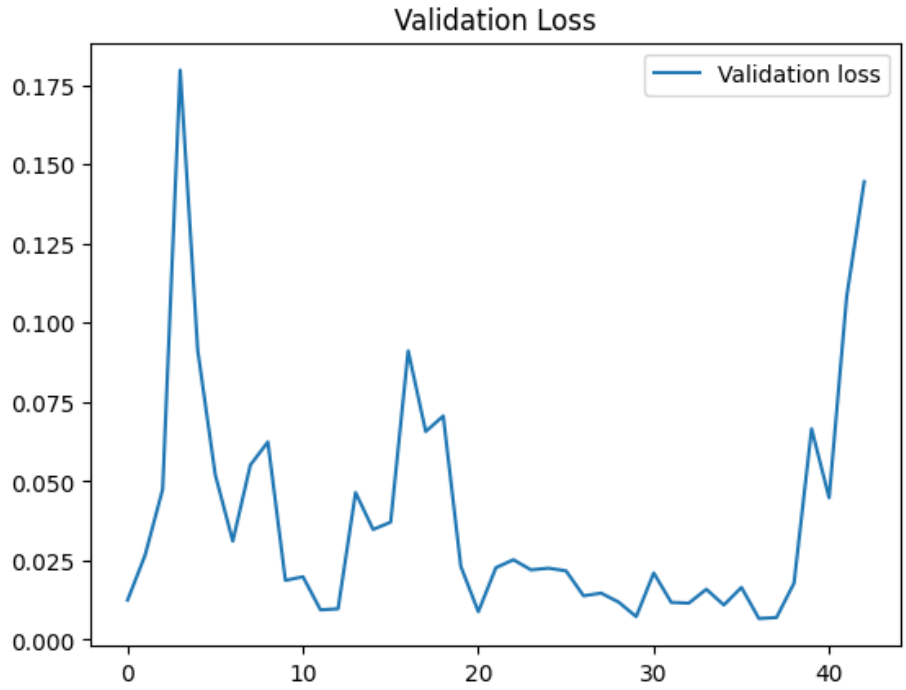

Figure 28: Validation MSE Loss

Closed Loop Actuation Results

- **Plots**:

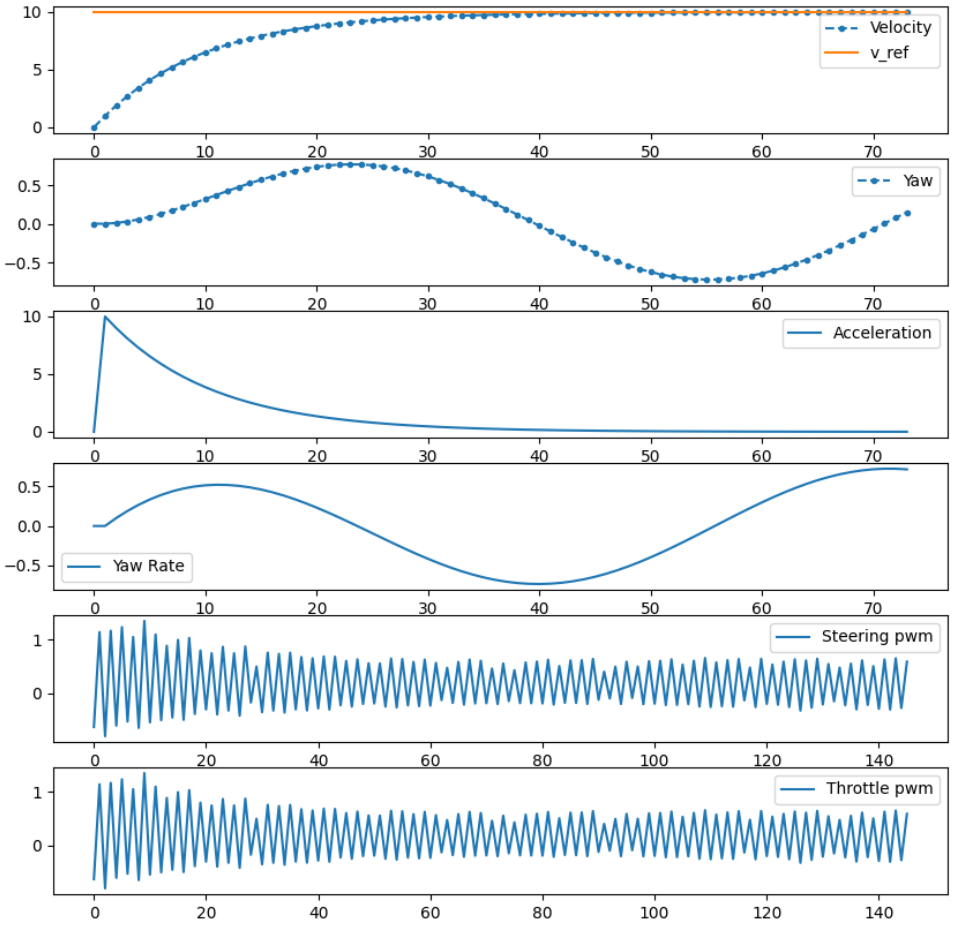

Figure 29: Controller Simulation plots

Result Summary

The neural network models developed and tested for calibrated actuation in lab-scale autonomous ground vehicles demonstrated varying levels of inference efficiency and predictive accuracy. Among them, PyTorch models generally exhibited faster inference times compared to their TensorFlow counterparts. Advanced architectures like LSTM and GRU provided robust performance in dynamic control tasks, making them suitable for real-time autonomous vehicle applications. Further optimization and research are necessary to address unresolved issues, such as adaptation to dynamic environments and managing the complexity of neural network architectures.

Challenges Faced

RESOLVED ISSUES

[Model Performance and Inference Efficiency]: Various neural network architectures including LSTM, GRU, and simple feedforward networks were evaluated for predicting throttle and steering PWM signals. The models showed competitive performance with respect to inference time and accuracy. Identified optimal neural network architectures for real-time control applications in autonomous vehicles.Models like LSTM and GRU demonstrated superior predictive capabilities with manageable inference times suitable for real-time applications. Optimization with TensorRT further improved efficiency. Identified optimal neural network architectures for real-time control applications in autonomous vehicles.

[Integration with ROS and Hardware Validation]:The integration of neural network controllers with ROS enabled effective communication and control between software components and physical vehicle hardware.ROS facilitated seamless data exchange and command execution, validating control algorithms in simulation and experimental settings.Demonstrated robustness and adaptability of the control system in practical scenarios.

[Comparative Analysis of Control Algorithms]: Conducted a comparative study between different control algorithms including MPC and LQR, alongside neural network-based controllers.Evaluated performance metrics such as trajectory tracking accuracy, response time, and computational efficiency.Established the effectiveness of neural network-based controllers in achieving precise actuation compared to traditional methods like MPC and LQR.

[Training and Validation]: Extensively trained and validated neural network models using both simulated and real-world data. Used training and validation sets to optimize model parameters and assess generalization capabilities.Achieved satisfactory performance metrics and validated control strategies for autonomous vehicle applications.

UNRESOLVED ISSUES

[Adaptation to Dynamic Environments]: Challenges remain in adapting neural network controllers to dynamic and unpredictable environments, such as varying road conditions, weather, and traffic scenarios. Further research is needed to enhance adaptability and robustness of control algorithms in real-world conditions where inputs may vary significantly.

[Complexity and Training Data Requirements]: Managing the complexity of neural network architectures and the high volume of training data required for op-

timal performance.Future work could focus on reducing model complexity without compromising accuracy and exploring techniques for efficient data collection and labeling.

[Safety and Certification]: Addressing safety concerns and meeting certification standards for deploying autonomous vehicles with AI-driven control systems.Continued efforts are necessary to ensure reliability, fail-safe mechanisms, and regulatory compliance in autonomous vehicle technologies.

[Real-Time Optimization and Control]: Enhancing real-time optimization capabilities of neural network controllers to handle rapid changes in vehicle dynamics and operational conditions.Research could explore adaptive learning algorithms approaches to improve responsiveness and decision-making in dynamic environments.

Conclusion

In this project, we explored the integration of neural network-based controllers for achieving calibrated actuation in lab-scale autonomous ground vehicles. Our approach involved designing and evaluating several models to predict throttle and steering PWM signals based on vehicle dynamics and control inputs. Here are the key findings and conclusions drawn from our study:

Firstly, we implemented multiple neural network architectures including LSTM, GRU, and simple feedforward networks to learn the mapping between vehicle states (such as acceleration, yaw rate) and control outputs (throttle and steering PWM). Each model was trained and evaluated using TensorFlow, PyTorch, and optimized using TensorRT to achieve efficient inference times suitable for real-time applications.

Secondly, through rigorous experimentation and comparative analysis, we observed that while more complex models like LSTM and GRU offer enhanced predictive capabilities, simpler architectures also provided competitive performance with significantly lower computational overhead. The choice of model architecture and optimization strategy significantly impacted both the inference time and overall control accuracy.

Additionally, the integration of ROS (Robot Operating System) facilitated seamless communication between the control nodes and the physical vehicle, enhancing the robustness and adaptability of our control system in varied operational scenarios.

Furthermore, our study validated the effectiveness of neural network-based controllers in achieving precise and calibrated actuation, crucial for the maneuverability and operational safety of autonomous ground vehicles. The models demonstrated robust performance in simulation and experimental validation, showcasing their potential for real-world deployment.

In conclusion, this project contributes to advancing the field of autonomous vehicle control by demonstrating the feasibility and effectiveness of neural network-based controllers for calibrated actuation. Future work could explore further optimization strategies, incorporate additional sensor inputs, and extend the study to larger-scale autonomous vehicle platforms.

Overall, our findings underscore the transformative potential of advanced machine learning techniques in enhancing the autonomy and operational efficiency of ground-based robotic systems.

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