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A Comprehensive Overview on Performance of Cascaded Three Tank Level System using Neural Network Predictive Controller

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ABSTRACT- A Neural Network Predictive Controller (NNPC) is a deep learning-based controller (DLC) that uses artificial neural networks (ANN) to predict the future behavior of a system and accordingly control its outputs. In this paper, an NNPC was used to predict the level of the three cascaded tank and then adjust the inputs as flow rate to maintain the desired level in the tank. A three-tank level system is a system consisting of three interconnected tanks used to store liquids. To achieve the desired level, the NNPC first collects data on system behavior, including inputs and outputs, and uses this data to train the neural network. The trained network was then used to make predictions about the future level of each tank and to generate control signals to adjust the inputs as needed. NNPC also incorporates feedback from the system to continuously refine its predictions and improve its control performance over time. The mean squared error (MSE) of different backpropagation training algorithms available in MATLAB deep learning toolbox were evaluated and presented. Based on the MSE and best validation, Levenberg Marquardt algorithm were used in NNPC controller for further step response tracking. Different performance metrics were evaluated and presented.

Keywords: Process control system; deep learning; backpropagation; three tank level system; artificial neural network; PID control.

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1. INTRODUCTION

Benchmark problems in process control systems are standardized test cases that are used to evaluate the effectiveness of different control methods. These benchmark problems typically involve simulating a process control system with known dynamics and disturbances, and then measuring the performance of different control strategies in terms of various metrics such as set-point tracking [1], [2], disturbance rejection, and stability. There are several well-known benchmark problems in process control systems, including: the Tennessee Eastman Process (TEP) two tanks, three tanks level system, the distillation column, the batch reactor etc. [3]. These benchmark problems are widely used in the process control community to compare the performance of different control strategies and algorithms. They provide a standardized and objective way to evaluate the effectiveness of different approaches and can help to identify areas where further research is needed. The research article [3] emphasizes the importance of benchmark problems in evaluating and comparing different soft computing methods. The article also provides an overview of several existing benchmark problems used for soft computing-based system identification and control.

A three-tank system [4] refers to a system consisting of three interconnected tanks used to store liquids or gases. The tanks were designed to work together to control the levels of liquids they contained. The system can be used in various industrial applications, such as water treatment, chemical processing, and fuel storage [3]. The tanks can be connected by pipes and valves that allow liquids to be transferred between them. Several approaches can be used for level control in a three-tank system: proportional-integral-derivative (PID) control [5], variations in PID controllers including parallel PID, series PID, cascade PID, model-based PID [6], [7],[8], fuzzy logic control, optimal control, and neural network-based control [9]. The use of PID control for level regulation in a cascaded three-tank system can present several challenges, such as: Difficulty in achieving good control performance due to the complex and nonlinear behavior of the system [10]. Challenges in tuning [11], [12], the PID parameters to account for the dynamics of the system and disturbances, which can lead to suboptimal performance. Limited adaptability to changes in the system, such as variations in the setpoint or disturbances, which can cause the controller to become unstable or inefficient. Difficulty in handling constraints and optimizing performance indices, such as

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minimizing overshoot or settling time, while accounting for practical limitations such as actuator saturation. Difficulty in achieving optimal performance, as the PID controller may not be able to handle constraints or optimize the performance index of the system efficiently [8]. The article [2] The first article proposes a new approach to designing a DLC for nonlinear systems by using a DNN to approximate the law using input-output data obtained from simulations of the system. The DNN is incorporated into a closed-loop control system that uses the Lyapunov stability criterion to ensure stability. Simulation results are presented for two nonlinear systems.

The article [13] discusses the application of deep learning techniques in instrumentation and measurement processes. The article provides an overview of deep learning concepts and techniques, including CNNs, RNNs, and DBNs, and their applications in various measurement systems such as image and signal processing, sensor networks, and automatic inspection systems. The article also discusses the challenges and limitations associated with deep learning in instrumentation and measurement and proposes possible solutions to overcome them. The deep learning controller [14], [15] outperforms traditional control methods and can effectively stabilize the nonlinear systems. An AI-based controller [2], [16]–[19] for the level control of a three-tank cascaded level system can provide significant benefits over traditional control methods [20] but they were not discussed the different time response and error indices performance parameters. By leveraging the power of artificial intelligence, an AI-based controller can improve control performance and provide more accurate and effective control of the levels in each tank [21], [22]. This can lead to more efficient and effective industrial processes and improved overall performance [23]. There is a lack of detailed survey in the existing literature on the applications of deep learning in process control. Additionally, the methodology to devise layers in a deep learning network is not sufficient, particularly in the field of process control systems. This suggests that further research is needed to explore the potential of deep learning in process control system and to develop effective methods for designing deep learning networks in this field. So, to overcomes the above limitations discussed, in this paper, an AI-based neural network predictive controller (NNPC) [24] was used to analysis the cascaded three-tank level system under the different training algorithms [25]–[28] and finally was used to find the step response of the three-tank system and to evaluate the different performance parameter [29], [30] including signal statistics, i.e., RMS, mean, median and time response analysis different error indices like ITAE, ITSE and IAE.

2. MATERIAL AND METHOD

2.1 Modeling of the Cascade Three-Tank Level Process

A three-tank system is a key component in many industrial processes, and its level control is essential to ensure safe and efficient operation. The level control of tanks is critical for ensuring the stability and safety of the system [3], [4]. The three-tank level process system typically consists of three interconnected tanks that are used to control the level of liquid in a process [4] [31]. The level of liquid in each tank is measured using sensors, and the information is used to control the flow of liquid into and out of the tanks [32], [33]. Controlling the level in a three-tank level process system is important for several reasons, including: process efficiency, product quality, safety, regulatory compliance [34] [35].

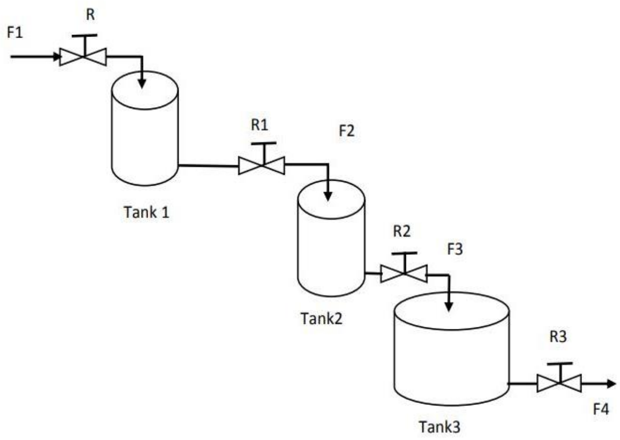

Figure 1: Cascaded three-tank non-interacting level process

At a steady state the level remains constant. Suppose that the flow rate of the liquid in the tank is altered at t=0. As a result, the liquid level and rate at which it drains change. The material balance for a single tank yield [36]:

$$q_i\rho - q\rho = \frac{d(\rho A_1 h_1)}{dt} \tag{1}$$

$$\rho(q_i - q) = \rho A_1 \frac{d(h_1)}{dt} \tag{2}$$

$$A_1 \frac{d(h_1)}{dt} = q_i - \frac{h_1}{R_1} \tag{3}$$

Similarly, for tanks 2 and 3, the dynamic equation can be written as:

$$A_2 \frac{d(h_2)}{dt} = \frac{h_1}{R_1} - \frac{h_2}{R_2} \tag{4}$$

and

$$A_3 \frac{d(h_3)}{dt} = \frac{h_2}{R_2} - \frac{h_3}{R_3} \tag{5}$$

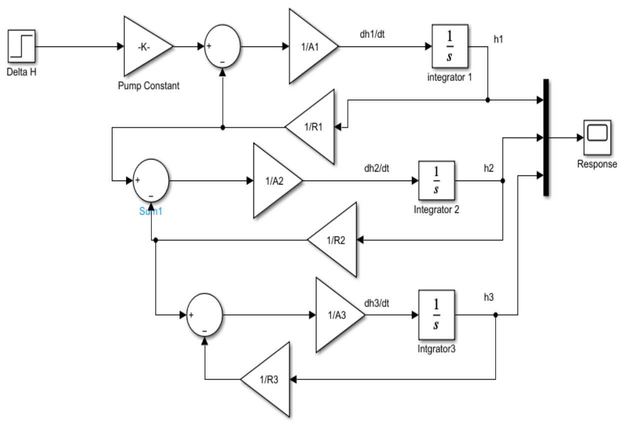

Figure 2: Simulink model of a cascaded three-tank system

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Using the deviation variable, the transfer function for cascaded three-tank non-interacting system is given as:

$$\frac{H_3(s)}{F_1(s)} = \frac{R_3}{(A_1R_1s+1)(A_2R_2s+1)(A_3R_3s+1)} \quad (6)$$

Considering $A_1 = A_2 = A_3 = 3\ m^2$, $R_1 = R_2 = R_3 = 40\ (m/(m^3/s))$

$$\frac{H_3(s)}{F_1(s)} = \frac{4}{8s^3+12s^2+6s+1} \quad (7)$$

2.2 Work Methodology

The Neural network-based control is a modern control approach [37] that uses artificial neural networks to model and control dynamic systems. A Neural Network Predictive Controller (NNPC) is a type of control approach that uses a neural network to predict the future behavior of a cascaded three tank system and generate control inputs accordingly. In a three-tank system, the NNPC can be used to control the levels of the tanks by predicting future tank levels and adjusting the control inputs to maintain the desired levels. The basic steps for NNPC in a three-tank system are as follows:

System modelling: Develop a mathematical model that describes the dynamics of the three-tank system, including the physical characteristics of the tanks, fluid flow rates, and valve dynamics as explained in equations (1-6) and *figure 2*.

Data collection: Collect data from the system, including the input and output signals, to use for training and validating the neural network model, as shown in *figure 4*. All data were generated in Simulink using the mathematical model of the three-tank level system.

Neural network design: Choose an appropriate neural network architecture and design the input and output. The hidden layers and neurons in the network should be selected based on the system's complexity and the amount of available data [38]. Multilayer feedforward neural network (MFNN) architecture is used in this work. The MFNN architecture is well-suited for Neural Network Predictive Control applications due to its ability to handle nonlinear relationships, learn from examples, process data in parallel, handle noise and missing data, be easily modified and adapted, and generalize well to new data.

Training the neural network: The neural network is trained with the data collected, by iteratively adjusting the weights and biases of the network to improve the accuracy of the predicted outputs, reducing the discrepancy between them and the true outputs of the system [25]. This step may involve dividing the data into testing, validation and training sets and using techniques such as backpropagation to update the weights of the network [30]. There are different backpropagation algorithms [39], a few of which are presented in *table 1*.

Predictive control design: Develop a predictive control algorithm that uses a neural network model to predict the future behavior of the system and generate control actions to maintain the desired level setpoints. The algorithm should account for constraints on the control inputs and outputs and be designed to achieve the desired control performance.

Testing and validation: Test the control system on a real system and validate its performance. This step may involve comparing the system's outputs with the desired setpoints and measuring performance metrics, such as rise time and steady-state errors etc.

Deployment: Once the control system has been validated, it can be deployed on the real system, and its performance can be monitored and adjusted as necessary [40].

NNPC can provide improved performance compared with traditional control methods, especially in complex and nonlinear systems. However, NNPC requires a significant amount of data and computational resources [41], and it can be more difficult to interpret the results of NNPC compared with traditional control methods. The best approach depends on the specific requirements of the three-tank system and the availability of data and computational resources.

3. RESULTS AND DISCUSSION

The open loop step response of the cascaded three-tank system shown in *figure 3* depicts the information that corresponds to the content presented in *figure 2*. The level height of tanks 1, 2 and 3 are denoted as h1, h2 and h3, respectively. The initial height of the tanks was considered as 1. Therefore, the level started increasing from 1 and reached a steady state. The level of the tanks reached a steady state at approximately after 800 seconds. Therefore, the simulation was run for 1200 seconds. The *figure* also shows that the time constant of the first tank is less than that of the second, and the time constant of the second tank is less than the third. Therefore, the level of the third tank was considered and analyzed further using the closed-loop response with NNPC. The simulation was run using different backpropagation training algorithms for evaluating the best performance. The performance of different backpropagation training algorithms is presented in the *table 1*. The simulation of some important backpropagation training algorithms is presented in *table 1*.

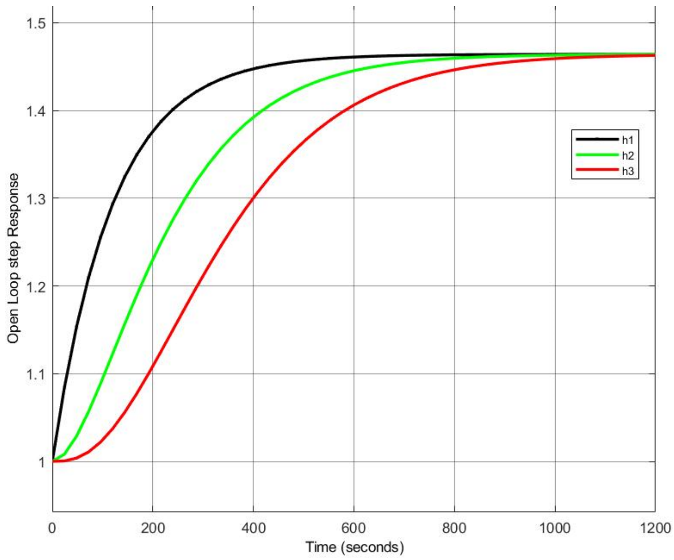

Figure 3: Open loop step response of the system

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The MATLAB deep learning toolbox provides a wide range of important training algorithms for deep learning models as presented in *table 1*. The Levenberg-Marquardt (LM) algorithm is a powerful optimization algorithm that can help improve the performance and generalization ability of neural networks. Its fast convergence, robustness, and built-in support in MATLAB make it an attractive option for researchers and practitioners working with deep learning models. The MSE of the LM training algorithm obtained were best, and hence, the LM training algorithm was used for further system analysis.

Table 1: Important training algorithms available in MATLAB deep learning toolbox

Sr. No.	Training Algorithm	MSE as a Performance		Best Validation Performance	
		MSE	at epoch	MSE	at epoch
1	trainlm	$9.36*10^{-6}$	45	$6.895*10^{-6}$	40
2	trainbfg	$2.49*10^{-4}$	1000	$1.7580*10^{-4}$	1000
3	trainbr	$7.830*10^{-6}$	1000	$7.836*10^{-6}$	100
4	traincgb	$4.220*10^{-4}$	3	$3.226*10^{-4}$	2
5	traincgf	$4.350*10^{-4}$	3	$2.750*10^{-4}$	2
6	traincgp	$4.110*10^{-4}$	5	$2.846*10^{-4}$	3
7	traingd	$5.610*10^{-4}$	6	$3.444*10^{-4}$	0
8	traingdm	$5.610*10^{-4}$	6	$3.444*10^{-4}$	0
9	traingda	$4.010*10^{-4}$	40	$2.60*10^{-4}$	37
10	traingdx	$4.180*10^{-4}$	30	$2.850*10^{-4}$	27
11	trainoss	$3.80*10^{-4}$	11	$2.593*10^{-3}$	5
12	trainrp	$5.610*10^{-4}$	6	$3.4449*10^{-4}$	0
13	trainscg	$1.210*10^{-4}$	56	$8.1356*10^{-5}$	50

Table 2: **Error indices of the system**

Error Indices	RMS	IAE	ISE	ITAE	ITSE
NNPC (corresponding to Figure 5)	0.095	21.60	21.46	330.0	205.0
NNPC (corresponding to Figure 6)	0.176	12.21	7.931	231.7	48.8

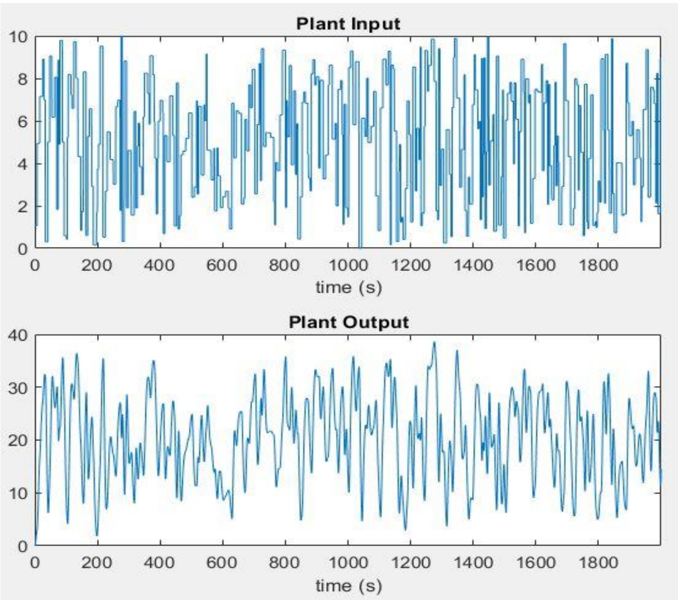

Figure 4: Graphical representation of training data

Graphical representation of training data is shown in *figure 4*. In this case, a mathematical model of the system is used to generate a large amount of training data, which can be used to train the neural network. The step response with a magnitude 2 of the system is shown in *figures 5* and *6*. *Figure 5* shows that the hidden layer and tuning, prediction horizon and control horizon were not properly selected. Corresponding to *figures 5* and *6*, the value of different error performances is presented in *table 2*. These values were evaluated for 50 seconds. The NNPC response corresponding to *figure 6* has lower error indices than the NNPC response corresponding to *figure 5*, indicating that the second response is more accurate and having less errors indices. *Figure 7* illustrates the control signal that corresponds to the data presented in *figure 6*. In *figure 5*, the peak value is near about four which is approximately twice the reference value of two and hence not recommended whereas in *figure 6*, the peak value is only near to 2.2 and hence overshoot is less than the previous one.

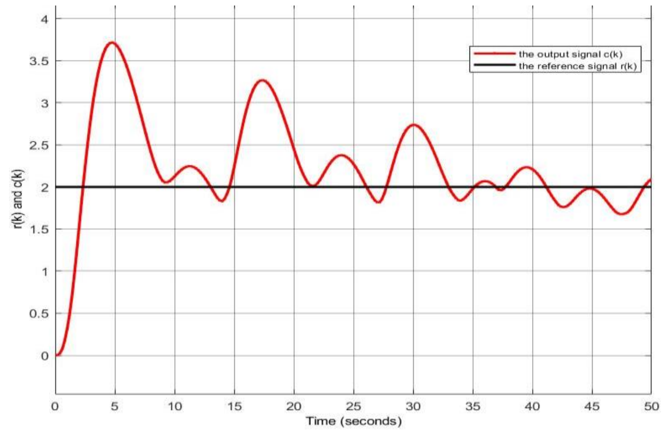

Figure 5: Step response with magnitude 2 of the cascaded three-tank system

A neural network predictive controller uses the predictive model to adjust the inflow rates of each tank to track an abrupt modification in the set point value of the tank, as shown in *figure 8*. Signal statistics of the response typically refers to the statistical analysis of the data obtained from the signal of interest. This can include measures such as mean, median, rise time, overshoot etc.

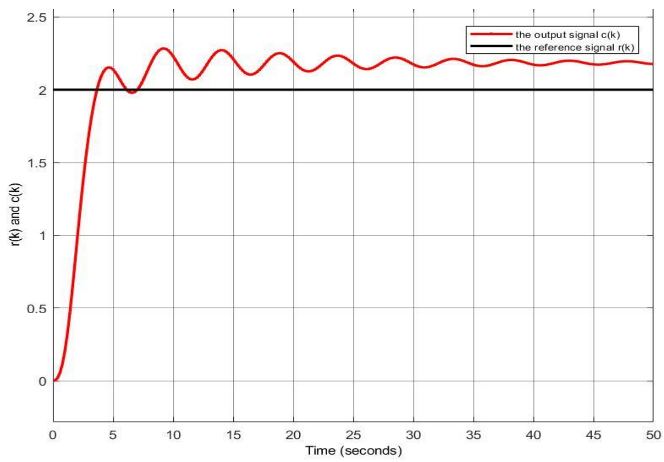

Figure 6: Step response with magnitude 2 with improved performance of the cascaded three-tank system

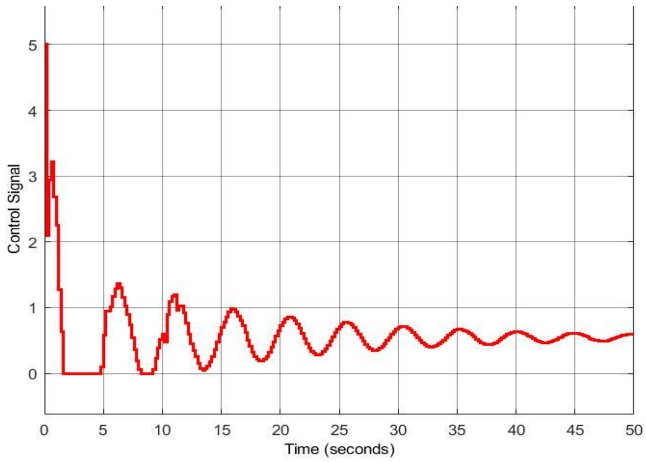

Figure 7: Control signal associated to Figure 6

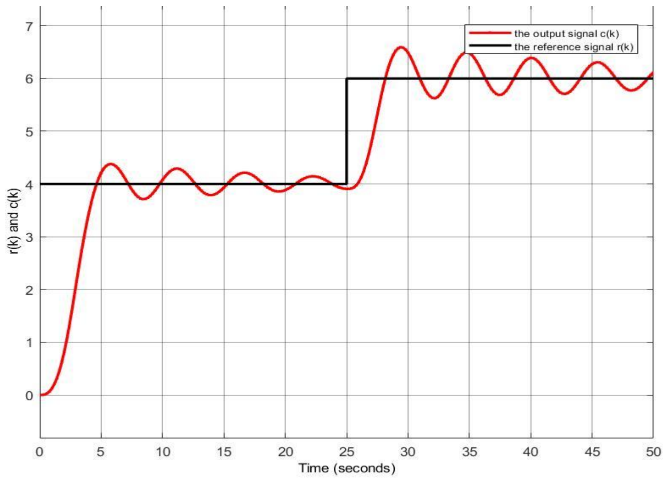

Figure 8: Set point tracking of the cascaded three-tank system using NNPC

Table 3: **Signal characteristics corresponding to *figure 6***

Sr. No.	Parameters	NNPC	PID
1	Peak Value	2.220	2.258
2	Mean Value	2.018	1.87
3	Median Value	2.174	2.00
4	RMS Value	2.080	1.927
5	Rise Time (s)	2.524	3.241
6	Peak Time (s)	6.200	6.710
7	Overshoot	4.73%	6.152%

By observing the *table 3*, we can conclude that signal characteristics of the system are good as RMS, median and mean value closes to ideal value *i.e.*, 2 for step response of magnitude 2. Also, the rise time is only 2.524 s and overshoot are near about 4.7 % and can be in the limit range. Based on the comparison between the NNPC and PID systems in the *table 3*, the NNPC system has advantages over the PID system, such as a higher median value, lower rise time and a lower overshoot. Hence deep learning based NNPC can be successfully applied to the process control system.

4. CONCLUSIONS

A level control system for a three-tank system can be designed using various control strategies, PID, LQR, MPC and NNPC. The choice of control strategy depends on the system's dynamics, objectives, and constraints. Proper design and tuning of the control system can ensure stability and performance. NNPC utilizes an ANN model to produce appropriate control inputs by anticipating future behavior. Designing an NNPC involves several steps, including system modeling, data collection, neural network design, training, predictive control design, testing, and deployment. Proper tuning of parameters like the prediction horizon and control horizon can improve control performance and reduce steady-state errors. By observing the *tables 1-3*, and from *figures 3-8*, we can conclude that signal characteristics of the system are good as RMS, median and mean value closes to ideal value i.e., 2 for step response of magnitude 2. Also, the rise time is only 2.524 s and overshoot are near about 4.7 % and can be in the limit range. The NNPC has a shorter rise time of 2.524 seconds compared to the PID's 3.241 seconds. Hence deep learning based NNPC can be successfully applied to the process control system. However, proper tuning of the controller's parameters is critical to achieving optimal control performance. During the designing of the controller, NNPC requires a large amount of data and computational resources, requires significant effort and time to train and tune, making it challenging to ensure optimal performance making it a complex and time-consuming process.

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