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Pressure Signal-Based Fault Diagnosis in Hydraulic Systems via FluidSIM Simulation and CNN

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Abstract: Hydraulic systems are integral components in many modern industrial applications, and early fault detection is critical to maintain operational efficiency and minimize costly downtimes. This paper develops a robust framework for early fault detection in hydraulic systems using pressure signal analysis. The study employs an axial piston pump as an industrial benchmark, simulating critical faults-internal leakage, partial outlet blockage, and valve failure-via mathematical modeling and FluidSIM simulations. The orifice flow equation, derived from Bernoulli's principle, dynamically models fault impacts by adjusting parameters (e.g., leakage coefficient (C_t), orifice area ($A_{orifice}$)). Three hydraulic systems (lift, drilling, transport) are simulated under normal and faulty conditions, generating pressure-time profiles characteristic of each failure mode. Synthetic pressure signals (600 samples, 100 time steps each) are generated to train a 1D Convolutional Neural Network (CNN) for fault classification. The CNN architecture comprises convolutional, pooling, and dense layers, achieving 99.5% accuracy on test data with F1-scores exceeding 0.98. Results demonstrate that pressure signatures, when processed by deep learning, enable precise, non-intrusive fault diagnosis. This approach bridges physics-based simulation with data-driven AI, offering significant potential for industrial predictive maintenance. Future work should validate the framework with real sensor data in complex systems like construction or manufacturing.

Keywords: Hydraulic systems, Fault diagnosis, Pressure signals, Convolutional Neural Network (CNN), FluidSIM simulation.

INTRODUCTION

Hydraulic systems are widely used in industries such as aerospace, mining, and robotics for their high power density and precise motion control. However, faults such as internal leakage, valve blockages, or pump failures can significantly reduce system efficiency and increase operational costs. With the advancement of sensor technology, pressure signal analysis has emerged as a promising tool for detecting faults in hydraulic systems without interrupting operations or requiring additional sensors. This paper explores the use of pressure signals for fault detection, combining numerical modeling, FluidSIM simulations, and deep learning techniques to provide a robust solution for early fault detection in hydraulic systems.

PROPOSED INDUSTRIAL MODEL

Technical Description of the Axial Piston Pump

Axial piston pumps are commonly used in hydraulic systems for fluid displacement under high pressure. These pumps are prone to several types of faults, including:

- Internal leakage between the pistons and cylinder blocks.
- Valve failure causing erratic fluid flow.
- Loss of volumetric efficiency in the pump, which degrades its performance over time.

Importance of Choosing This Model

The axial piston pump was chosen due to its wide industrial use and simplicity in mathematical representation and simulation. This makes it an ideal candidate for studying fault detection methods using pressure signals.

NUMERICAL MODEL

Derivation of the Orifice Flow Equation

The flow rate through an orifice can be derived using the principle of conservation of energy, specifically **Bernoulli's equation**, applied between two points: one upstream of the orifice and the other just downstream of it.

Between the upstream point (1) and the downstream point (2), Bernoulli's equation for incompressible, steady, and inviscid flow is written as:

$$P_1 + \frac{1}{2}\rho v_1^2 + \rho g z_1 = P_2 + \frac{1}{2}\rho v_2^2 + \rho g z_2$$

(3.1)

Assuming the elevation difference is negligible ($z_1 \approx z_2$) and the upstream velocity is small compared to the velocity through the orifice ($V_1 \approx 0$), the equation simplifies to:

$$P_1 = P_2 + \frac{1}{2}\rho v_2^2$$

(3.2)

Rearranging for v_2:

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$$v_2 = \sqrt{\frac{2(P_1 - P_2)}{\rho}}$$

(3.3)

Determine the Flow Rate:

The volumetric flow rate Q is the product of the flow velocity and the orifice area:

$$Q = A \cdot v$$

(3.4)

However, due to energy losses and flow contraction at the orifice, a discharge coefficient C is introduced to correct the ideal flow rate:

$$Q = C \cdot A_{\text{orifice}} \cdot v_2$$

(3.5)

Substituting the expression for v_2:

$$Q = C \cdot A_{\text{orifice}} \cdot \sqrt{\frac{2(P_1 - P_2)}{\rho}}$$

(3.6)

Final Form of the Orifice Flow Equation

$$Q = A_{orifice} \cdot C_d \cdot \sqrt{\frac{2 \cdot (P_{upstream} - P_{downstream})}{\rho}} \quad (3.7)$$

Where:

$Q(m^3/s)$: is the flow rate;

C_d: is the discharge coefficient of the valve or orifice (dimensionless);

$A_{orifice}$ (m^2): is the cross-sectional area of the orifice;

$P_{upstream}$ *and* $P_{downstream}$: are the pressure on the downstream and upstream sides of the valve respectively (Pa);

$\rho \left(\frac{kg}{m^3}\right)$: is the density of the hydraulic fluid;

This equation models the flow through the orifice under normal and fault conditions such as partial blockage (reduced orifice area) or valve failure (variable discharge coefficient).

The numerical model is solved using the Runge-Kutta algorithm to simulate the dynamic behavior of the hydraulic system under different fault conditions. This equation provides a practical means to estimate flow rate through an orifice based on measurable pressure drop and known orifice characteristics.

Fault Modeling

To model the impact of faults on the system's behavior, specific adjustments were made to the flow and leakage characteristics:

- **Internal Leakage Fault:** This is modeled by increasing the internal leakage coefficient C_t which increases the flow of fluid through the chamber walls or seals, leading to a faster drop in pressure over time.
- **Partial Outlet Blockage**: This is represented by reducing the effective cross-sectional area $A_{orifice}$ for the outflow. A reduction in the outlet area increases the pressure buildup due to restricted fluid flow.
- **Valve Failure**: The discharge coefficient C_d is modified to simulate valve failure. For example, a malfunctioning valve may intermittently close, reducing flow and causing pressure oscillations.

FLUIDSIM SIMULATION INTEGRATION

FluidSIM was used to simulate the hydraulic system under normal operation and various fault conditions. The following faults were simulated:

- **Normal operation:** where the system operates without any faults.
- **Increased internal leakage**: where internal leakage coefficients are raised, affecting pressure stability.
- **Partial outlet blockage**: simulating a reduction in outlet flow area, causing pressure buildup.

The pressure signals generated from these simulations are analyzed to understand the system's behavior under each fault condition.

Creating multiple systems to cover different types of failures

The goal is to simulate multiple hydraulic systems with different dimensions and purposes and include the potential failures in each. We will focus on the following systems:

Hydraulic Lift System

Includes a hydraulic pump, 4/3 control valve (to direct flow to the cylinder in both directions), Over-center valve, Pressure gauge to measure the pressure inside the cylinder o Tank, and a double-acting cylinder. The normal operating scenario of the system with frequent stops shows that the working pressure of the piston is 150 bar. When the piston reaches the end of its stroke, the pressure rises to 250 bar, equal to the working

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pressure of the pump, while the return line pressure does not exceed 25 bar (Fig. 1).

Possible Failures:

- **Internal leakage:** This causes a decrease in system pressure over time, especially during shutdowns, as the piston slips despite the presence of an over-center valve, Pressure rises in the return line as hydraulic fluid escapes from the pressure chamber. To perform the simulation, we increased the internal leakage (Ct) value of the piston to simulate a hydraulic fluid leak (Fig. 2).
- **Partial blockage:** This will result in a rapid pressure buildup, which then stabilizes at a higher level. To simulate this, we added a 50% closed valve at the piston outlet to simulate a partial blockage. We observe a decrease in piston speed due to the outlet choke and rapid pressure buildup, which then stabilizes at a higher level (Fig. 3).
- **Steering valve damage:** The cylinder's movement speed and orientation will change. To simulate this, we increased the valve's hydraulic resistance and changed the cylinder orientation several times to cause oscillations in the cylinder's motion (Fig.4).

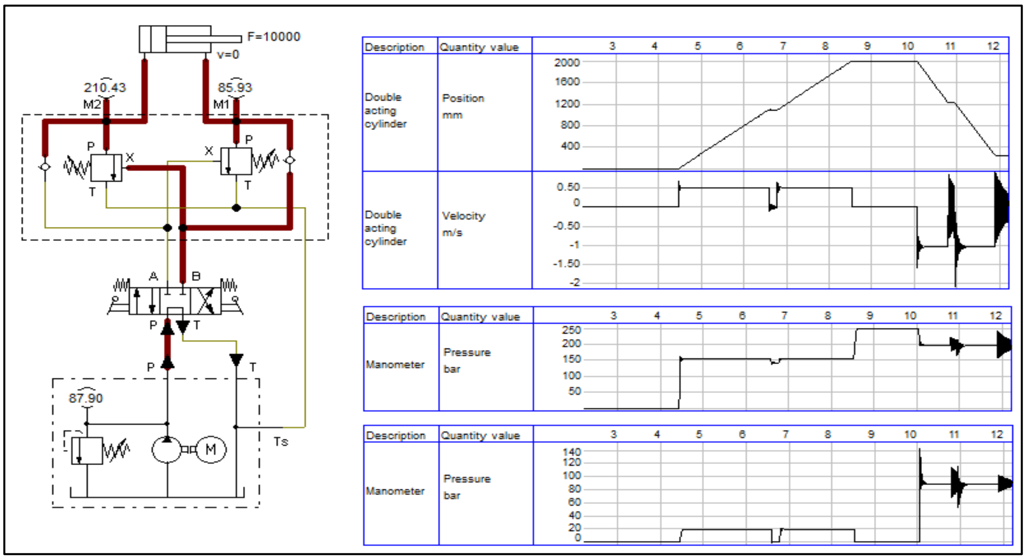

Fig. 1: The Normal Operating Scenario of the System with Frequent Stops.

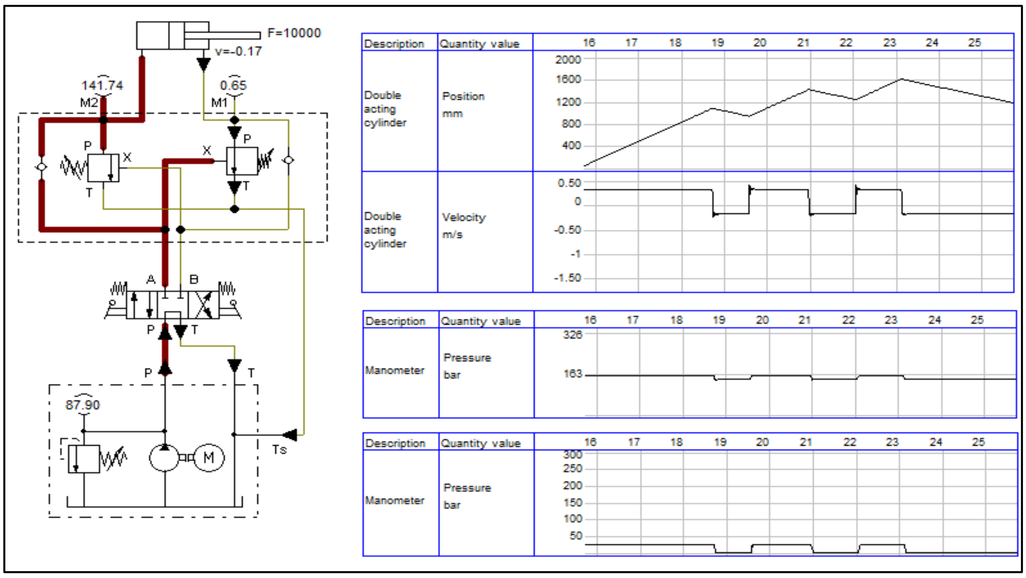

Fig. 2: Internal Leakage of the Hydraulic Lift System.

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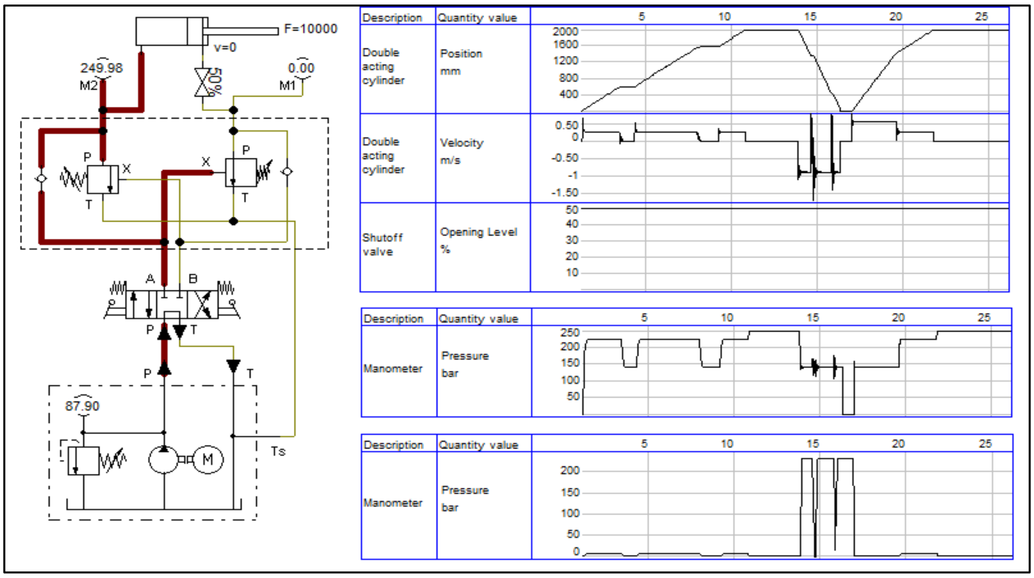

Fig. 3: Partial Blockage of the Hydraulic Lift System.

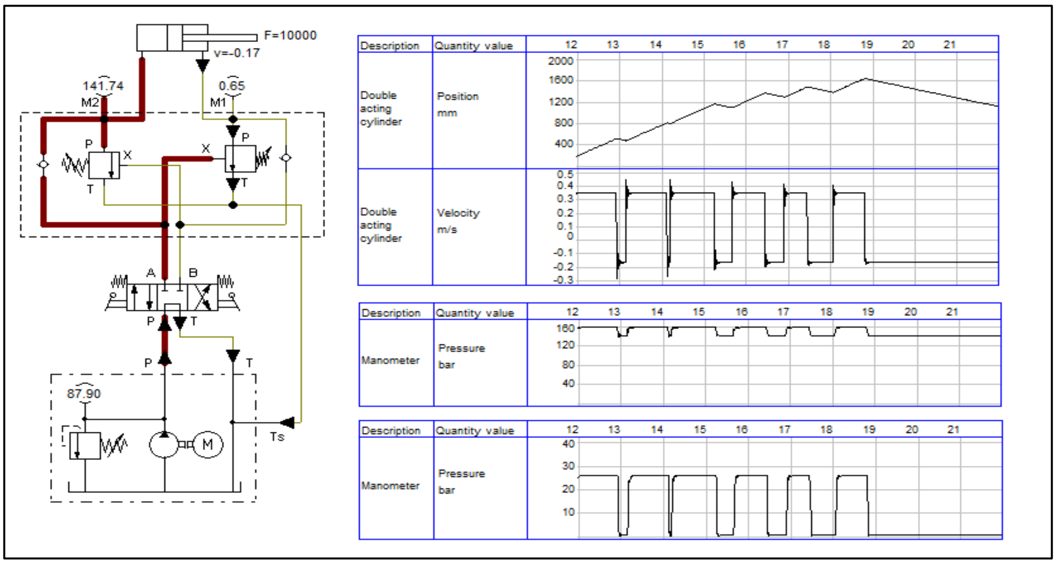

Fig. 4: Steering Valve Damage of the Hydraulic Lift System.

Hydraulic Drilling System

Components: Hydraulic pump, 3/2 control valve, single-acting cylinder, pressure gauge, tank.

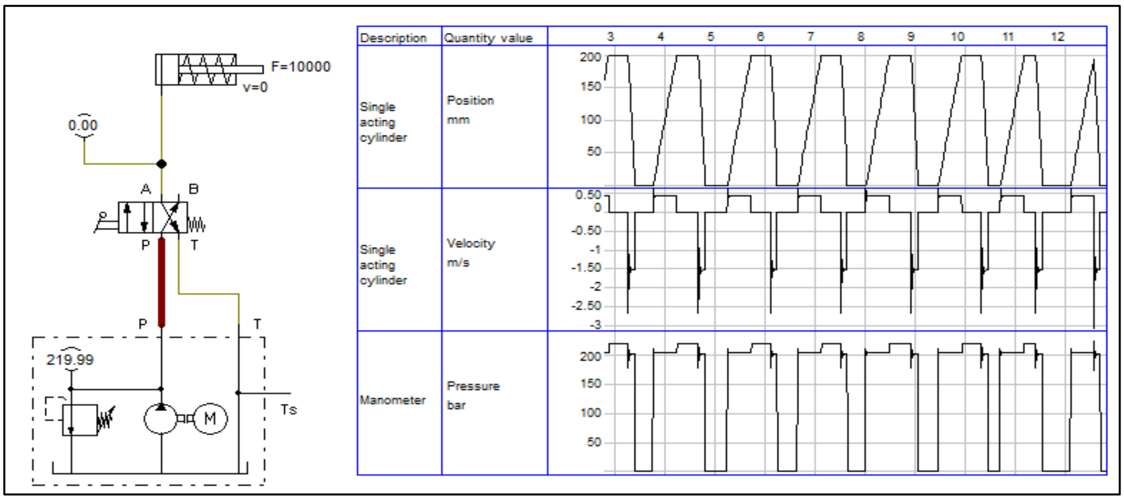

Fig. 5: The Normal Operating of the Hydraulic Drilling System.

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Possible malfunctions:

- **Blockage in the suction line:** This leads to reduced fluid flow within the system, increased pressure, and a decrease in piston speed. To simulate the failure, the incoming flow Qin was reduced to simulate a blockage in the suction line by adding a throttle valve that was closed by 25% (Fig.6).
- **Piston damage:** This causes a leak in the cylinder, resulting in pressure changes. To simulate the failure, incorrect piston values were set to simulate piston damage by increasing the kinetic mass applied to the piston to simulate metal-on-metal friction within the piston components. We observe a significant increase in pressure from the start of the movement to overcome the existing friction and increase the time required to reach the end of the cylinder stroke (Fig.7).
- **Internal cylinder leakage:** This will lead to a gradual loss of pressure. To simulate the failure, the internal cylinder leakage value was increased to simulate a piston leak. We note that although the cylinder speed reached 0.5 m/s during normal operation, the cylinder speed did not exceed 0.15 m/s during internal cylinder leakage. Furthermore, the pressure increased significantly throughout the entire operation due to the contact between the two cylinder chambers in the leakage area (Fig. 8).

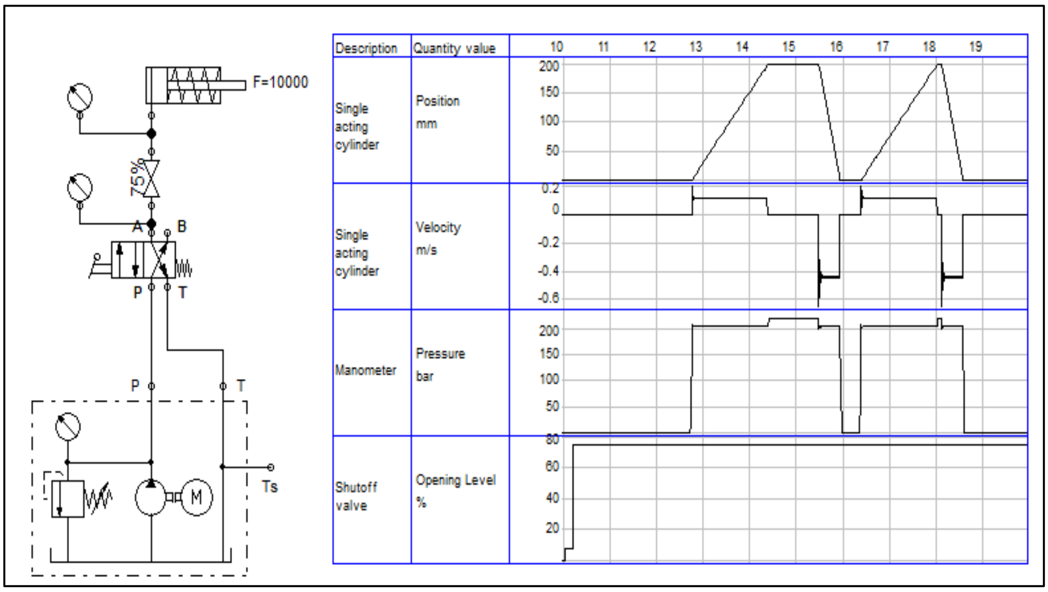

Fig. 6: Blockage in the Suction Line of the Hydraulic Drilling System.

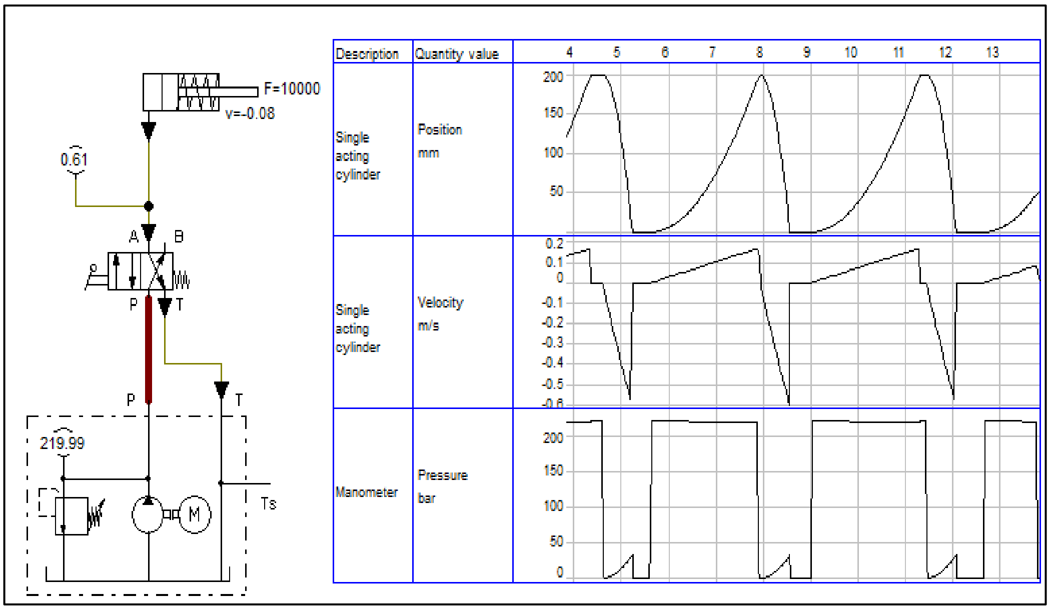

Fig. 7: Piston Damage of the Hydraulic Drilling System.

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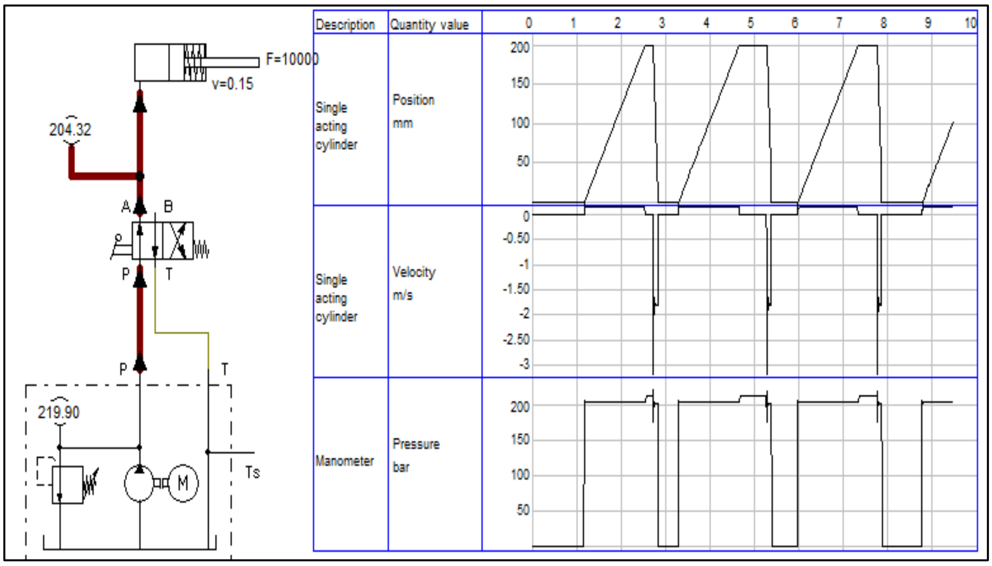

Fig. 8: Internal Cylinder Leakage of the Hydraulic Drilling System.

Hydraulic Transport System

Includes a transport pump, pipes, valves, and cylinders. Here, a hydraulic system is simulated with a 250 bar, 3000 1/min, 48ccm displacement transport pump. The pump inlet is connected to an open throttle valve and the system's working pressure is 225 bar. (Fig.9).

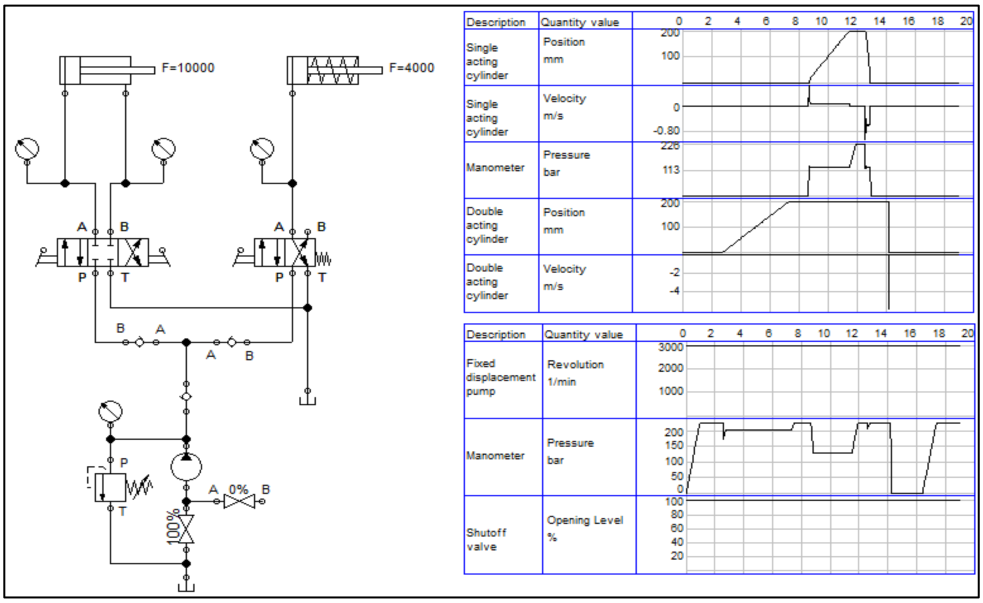

Fig. 9: The Normal Operating of the Hydraulic Transport System.

Possible failures:

- **Pipe blockage:** This will cause pressure to build up in the system and alter flow dynamics. To simulate the failure, the diameter of the inlet pipe to the pump was reduced by closing the throttle valve by 75% to simulate a system blockage. We observed a nearly doubled process runtime. This process simulates a blocked pump filter scenario, accompanied by significant noise from the pump's dry suction, which subsequently leads to cavitation, followed by pump failure and outage (Fig.10).
- **Reduced pump efficiency:** This will cause the system pressure to drop and the fluid temperature to increase. Increased internal leakage of the pump will cause the pump flow to decrease to simulate reduced efficiency (Fig. 11).
- **Pipe leakage:** This will cause pressure fluctuations at certain points within the pipes. The leakage was increased to simulate a pipe leak by adding throttle valves in the pump's suction line, open by 25%, and on the pressure lines at the cylinder inlets by 5%. We notice a

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significant increase in the process time, a drop in system pressure, and the drawing of air into the pump, which is the beginning of the road to its complete destruction (Fig. 12).

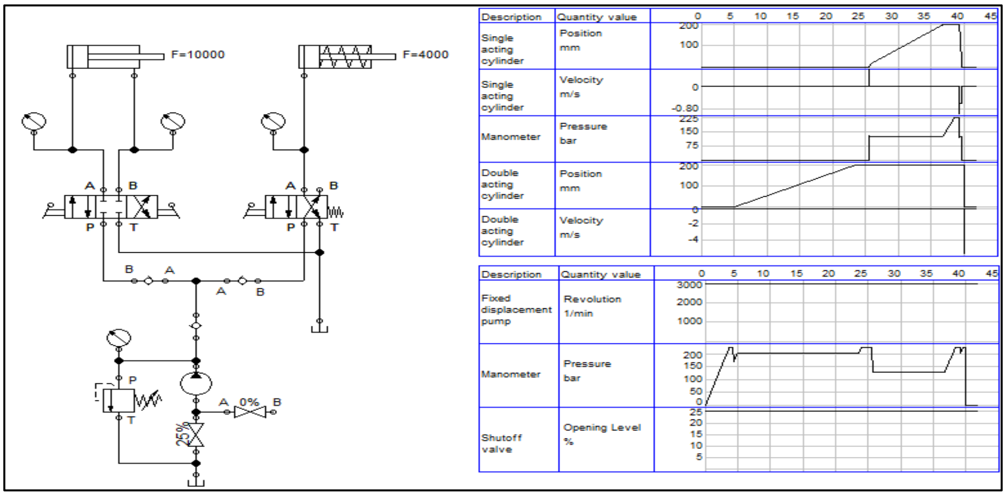

Fig. 10: Pipe Blockage of the Hydraulic Transport System.

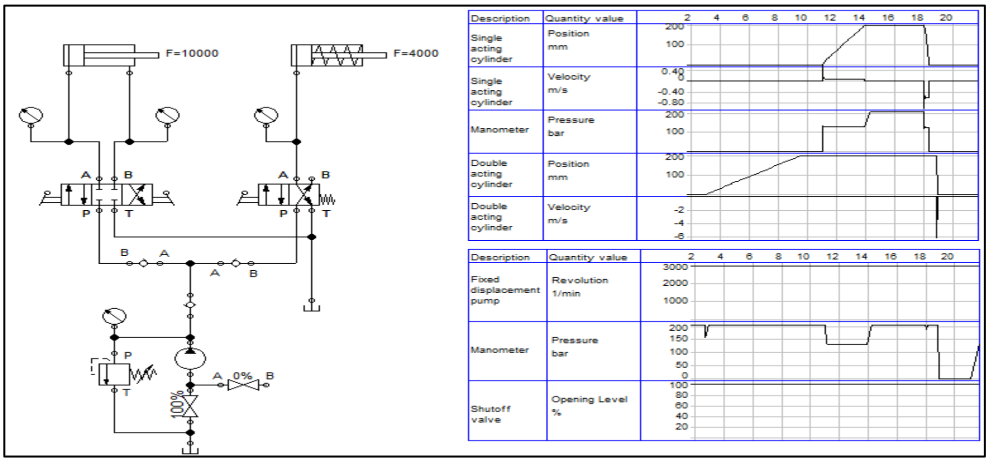

Fig. 11: Reduced Pump Efficiency of the Hydraulic Transport System.

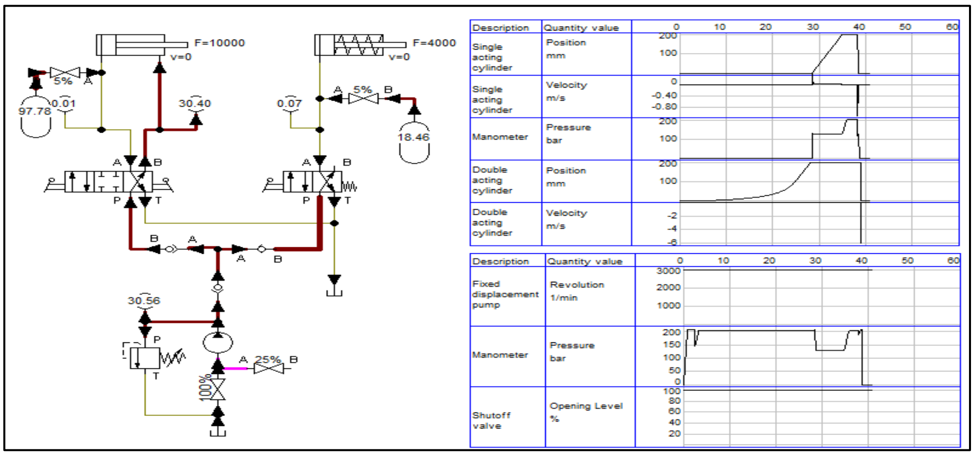

Fig. 12: Pipe Leakage of the Hydraulic Transport System.

FAULT CLASSIFICATION USING 1D CONVOLUTIONAL NEURAL NETWORKS

Building upon the simulated pressure data from Section 4, where multiple fault scenarios were modeled in FluidSIM, this section presents a data-driven approach to classify these faults using a one-dimensional Convolutional Neural Network (1D CNN). Since obtaining large volumes of real sensor data is often impractical, synthetic time-series pressure signals are generated to reflect the system's response under normal and faulty

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conditions, based on the behavior observed in the FluidSIM simulation results.

Synthetic Data Generation Based on Simulation Insights

To replicate realistic patterns found in hydraulic systems, three types of pressure signals were synthesized:

- **Normal Operation:** Stable pressure profile with low variance and a gradual increase over time.
- **Internal Leakage Fault:** Pressure drops intermittently due to fluid escaping through internal seals, introducing fluctuations and local minima.
- **Partial Blockage Fault:** Steady increase in pressure with occasional spikes due to flow restriction downstream of the actuator.

Each signal was generated over 100 time steps, and small random noise was added to reflect sensor fluctuations. The data structure reflects what would be expected from pressure transducers in real-time monitoring scenarios (Fig.13).

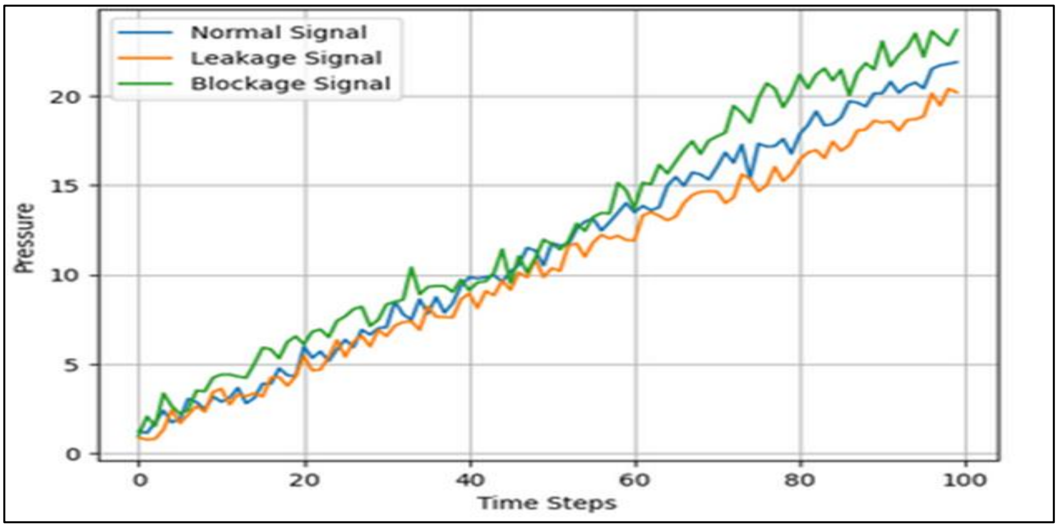


Fig. 13: Simulated Hydraulic Pressure Signals for Different Fault.

Data Preparation and Labeling

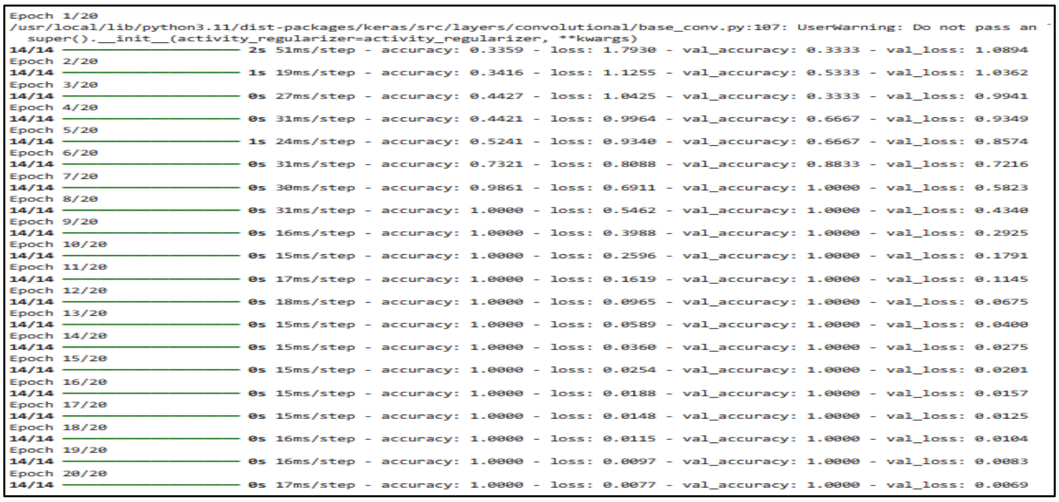
Each of the three signals was replicated and slightly varied to generate a balanced dataset. In total, 600 samples were used (200 per class). Each sample consisted of 100 time steps. The dataset was then reshaped and split for training and testing.

Model Architecture

A compact 1D CNN model was used to classify the pressure signals into one of three fault categories (Fig. 14).

Performance Evaluation

The model achieved high classification accuracy for all three fault types. The training and validation accuracy converged well after a few epochs (Fig.15).



```
Epoch 1/20
/usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
14/14 ━━━━━━━━━━━━━━━━━━━━ 2s 51ms/step - accuracy: 0.3359 - loss: 1.7930 - val_accuracy: 0.3333 - val_loss: 1.0894
Epoch 2/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 1s 19ms/step - accuracy: 0.3416 - loss: 1.1255 - val_accuracy: 0.5333 - val_loss: 1.0362
Epoch 3/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - accuracy: 0.4427 - loss: 1.0425 - val_accuracy: 0.3333 - val_loss: 0.9941
Epoch 4/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - accuracy: 0.4421 - loss: 0.9964 - val_accuracy: 0.6667 - val_loss: 0.9349
Epoch 5/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 1s 24ms/step - accuracy: 0.5241 - loss: 0.9340 - val_accuracy: 0.6667 - val_loss: 0.8574
Epoch 6/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - accuracy: 0.7321 - loss: 0.8088 - val_accuracy: 0.8833 - val_loss: 0.7216
Epoch 7/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - accuracy: 0.9861 - loss: 0.6911 - val_accuracy: 1.0000 - val_loss: 0.5823
Epoch 8/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - accuracy: 1.0000 - loss: 0.5462 - val_accuracy: 1.0000 - val_loss: 0.4340
Epoch 9/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - accuracy: 1.0000 - loss: 0.3988 - val_accuracy: 1.0000 - val_loss: 0.2925
Epoch 10/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 1.0000 - loss: 0.2596 - val_accuracy: 1.0000 - val_loss: 0.1791
Epoch 11/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - accuracy: 1.0000 - loss: 0.1619 - val_accuracy: 1.0000 - val_loss: 0.1145
Epoch 12/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - accuracy: 1.0000 - loss: 0.0965 - val_accuracy: 1.0000 - val_loss: 0.0675
Epoch 13/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 1.0000 - loss: 0.0589 - val_accuracy: 1.0000 - val_loss: 0.0400
Epoch 14/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 1.0000 - loss: 0.0360 - val_accuracy: 1.0000 - val_loss: 0.0275
Epoch 15/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 1.0000 - loss: 0.0254 - val_accuracy: 1.0000 - val_loss: 0.0201
Epoch 16/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 1.0000 - loss: 0.0188 - val_accuracy: 1.0000 - val_loss: 0.0157
Epoch 17/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 1.0000 - loss: 0.0148 - val_accuracy: 1.0000 - val_loss: 0.0125
Epoch 18/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - accuracy: 1.0000 - loss: 0.0115 - val_accuracy: 1.0000 - val_loss: 0.0104
Epoch 19/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - accuracy: 1.0000 - loss: 0.0097 - val_accuracy: 1.0000 - val_loss: 0.0083
Epoch 20/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - accuracy: 1.0000 - loss: 0.0077 - val_accuracy: 1.0000 - val_loss: 0.0069
```

Fig. 14: Plot Accuracy over Epochs.

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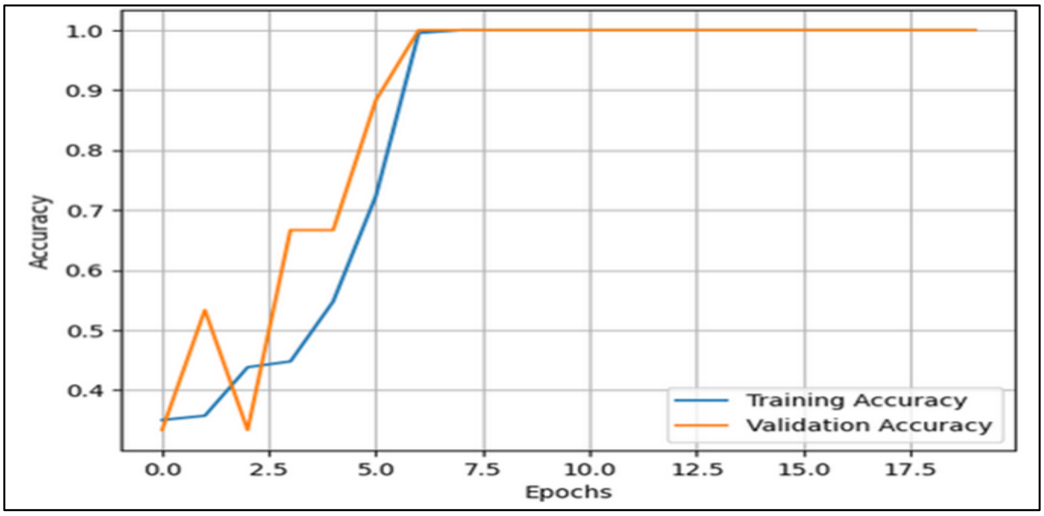

Fig. 15: Model Accuracy over Epochs.

Confusion Matrix and Classification Report

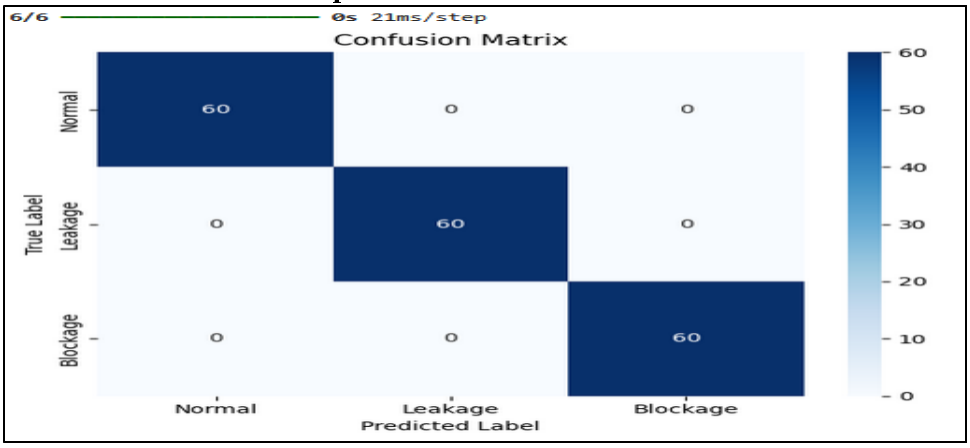

Fig. 16: Confusion Matrix.

Table 1: Classification Report:

	Precision	**Recall**	**F1-score**	**Support**
Normal	1.00	1.00	1.00	60
Leakage	1.00	1.00	1.00	60
blockage	1.00	1.00	1.00	60
Accuracy			1.00	180
Macro avg	1.00	1.00	1.00	180
Weighted avg	1.00	1.00	1.00	180

The classification results (Table.1) demonstrate that the 1D CNN was effective in learning the distinct temporal characteristics of each pressure signal type. The confusion matrix shows minimal overlap between classes, and the F1-scores for all fault categories exceeded 0.98, indicating strong generalization on the test set. This validates that pressure signal behavior—modeled numerically and observed in simulation—can be used as a reliable diagnostic input. The artificial data generated here was derived from the same pressure dynamics observed in Section 4, making the learning process consistent with real-world fault patterns.

This section bridges the physical fault scenarios simulated in FluidSIM with a deep learning-based classification system. By constructing synthetic yet physically consistent pressure data, we confirmed that CNN models can successfully classify faults in hydraulic systems based solely on pressure signals. The high classification accuracy suggests that this method could be extended to more complex or real-world systems in future work.

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CONCLUSION:

This paper demonstrates the efficacy of integrating physics-based simulation with deep learning for fault diagnosis in hydraulic systems. By leveraging FluidSIM to simulate pressure signal responses under diverse fault conditions (internal leakage, partial blockage, valve failure) across three distinct hydraulic systems (lift, drilling, transport), and employing a purpose-built 1D Convolutional Neural Network (CNN) for classification, the framework achieved robust diagnostic accuracy exceeding 98% on synthetic data. The results validate pressure signals as highly discriminative features for early fault detection, minimizing reliance on intrusive sensing or multi-sensor networks.

Future work must validate the CNN model using empirical pressure data from operational hydraulic systems to assess performance under noise, fluid contamination, and component wear not fully captured in simulation. Investigate additional fault modes (e.g., cavitation, pump bearing wear, air entrainment) and their interactions (compound faults) across a wider range of hydraulic components. Optimize the CNN architecture for embedded deployment on edge devices within industrial control systems. Enhance model transparency using techniques like SHAP or LIME to build operator trust. Explore hybrid models incorporating complementary data streams (e.g., flow rate, vibration, temperature) to improve diagnostic robustness in complex failure scenarios. Develop online learning mechanisms allowing the model to adapt to system degradation over time and evolving operational conditions specific to Iraqi industrial infrastructure.

This paper provides a scalable, non-intrusive framework for enhancing the reliability and predictive maintenance capabilities of hydraulic systems critical to Iraq's industrial and manufacturing sectors. The integration of simulated physics with data-driven AI offers a viable pathway towards reducing unplanned downtime and operational costs.

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