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# A ROBUST DEEP RESIDUAL LEARNING APPROACH FOR EARLY FAULT DETECTION, DIAGNOSIS, AND CONDITION MONITORING OF HYDRAULIC SYSTEMS

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Abstract

Hydraulic systems are widely used in industrial applications due to their reliability and high power density, but they are also prone to faults that can affect performance and safety. Accurate and timely fault detection is therefore essential for maintaining system efficiency. This study presents a deep residual learning-based model, referred to as DRL-HFDM, for intelligent fault detection in hydraulic systems. The proposed approach utilizes multi-sensor data, including pressure, temperature, and vibration signals, to capture system behavior under different operating conditions.The dataset used in this study was preprocessed and analyzed using both bivariate and multivariate techniques to understand the relationship between sensor parameters and fault conditions. The model was then evaluated against several advanced architectures, including Transformer-based, CNN–GRU, SE-ResNet, attention-based, and CNN–BiLSTM models. The experimental results show that the proposed DRL-HFDM model achieves an accuracy of 97.1%, precision of 96.7%, recall of 96.4%, and F1-score of 96.5%, outperforming all compared models.In addition to improved predictive performance, the model demonstrates stable training behavior and efficient handling of multi-sensor inputs. The results indicate that the proposed approach is effective in identifying fault conditions and can be applied in real-time monitoring systems. This makes it a suitable solution for industrial applications requiring reliable and accurate fault detection.

Keywords: hydraulic systems, fault detection, deep residual learning, multi-sensor data, predictive maintenance, machine learning, condition monitoring

## 1. INTRODUCTION

Hydraulic systems are widely used in industrial applications such as manufacturing, aerospace, and heavy machinery because of their ability to deliver high power with precise control. Their reliability and efficiency make them a preferred choice in critical operations. However, the same complexity that enables their performance also makes them vulnerable to faults. Issues such as leakage, wear, pressure fluctuations, and component degradation can gradually affect system performance and, if left undetected, may lead to unexpected failures, safety risks, and increased maintenance costs.

To address these challenges, fault detection has evolved from traditional rule-based and signal-processing approaches to more data-driven techniques. Conventional methods often rely on manual feature extraction and domain expertise, which limits their ability to handle complex and nonlinear patterns present in hydraulic signals. In contrast, recent advances in machine learning and deep learning have enabled automated feature extraction directly from raw sensor data, improving both accuracy and scalability.

Among these approaches, deep residual learning has emerged as a particularly effective solution. Residual networks (ResNet) introduce skip connections that allow information to flow more easily across layers, thereby overcoming issues such as vanishing gradients in deep architectures. This capability enables the model to learn richer and more discriminative features from hydraulic signals, even when the data is noisy or limited. As a result, residual learning has been increasingly applied in fault diagnosis tasks, demonstrating improved performance compared to conventional neural networks and shallow machine learning models.

At the same time, modern hydraulic systems generate data from multiple sensors, including pressure, flow rate, temperature, and vibration. Integrating these heterogeneous signals presents an opportunity to capture a more comprehensive representation of system behavior. However, it also

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introduces challenges related to data variability, synchronization, and computational complexity. Recent studies have attempted to address these issues through multi-sensor fusion and hybrid deep learning architectures, but limitations in generalization and real-time applicability still remain.

In this context, there is a clear need for a robust and scalable fault detection framework that can effectively learn from complex hydraulic data while maintaining computational efficiency. This study focuses on the use of deep residual learning for intelligent fault detection in hydraulic systems. The proposed approach aims to improve feature extraction, enhance classification accuracy, and provide a reliable foundation for practical deployment in industrial environments. Compared with existing hydraulic pitch system diagnostic approaches that primarily focus on model-based estimation or component-specific fault diagnosis, the proposed DRL-HFDM provides a generalized multi-sensor residual learning framework capable of simultaneously exploiting pressure, flow rate, vibration, and temperature information. The principal contribution is the integration of residual learning with comprehensive multi-sensor feature extraction under a unified deep learning architecture suitable for industrial hydraulic monitoring.

### 1.1.Contributions of thestudy

The main contributions of this study are summarized as follows:

First, a deep residual learning-based framework, referred to as the DRL-HFDM model, is proposed for intelligent fault detection in hydraulic systems. The model is designed to effectively capture complex patterns in hydraulic signals while maintaining stable training through residual connections.

Second, a structured signal representation approach is introduced to preserve temporal dependencies in hydraulic data. By incorporating positional encoding (as defined in Equations (1) and (2)), the model retains sequential information, which improves the quality of learned features.

Third, a residual learning mechanism is developed to enhance feature extraction from non-linear and noisy hydraulic signals. The adaptive weight update strategy (Equations (3)–(5)) enables the model to learn deeper and more discriminative representations compared to conventional approaches.

Fourth, physical system characteristics are integrated into the learning process through mathematical modeling of hydraulic parameters. The relationships defined in Equations (6)–(14) ensure that the model is not purely data-driven but also aligned with system-level behavior, improving reliability and interpretability.

Fifth, an optimization strategy is incorporated to improve convergence and avoid local minima during training. The update mechanisms described in Equations (15)–(18) provide a balance between exploration and exploitation, leading to improved model performance.

Finally, the proposed framework offers a unified approach that combines signal processing, deep residual learning, physical modeling, and optimization. This integration enables robust fault detection under varying operating conditions while maintaining computational efficiency, making the model suitable for practical industrial applications.

## 2.RELATED WORK

In recent years, research on fault detection in hydraulic systems has increasingly shifted toward data-driven approaches, particularly those based on deep learning. This transition is mainly driven by the limitations of traditional methods, which rely heavily on manual feature extraction and struggle to capture the complex and nonlinear characteristics of hydraulic signals. Deep learning models, on the other hand, are capable of learning representative features directly from raw data, making them more suitable for real-world industrial environments.

One of the widely explored directions in this domain is the use of residual learning. Residual networks have shown strong performance in fault diagnosis tasks due to their ability to train deeper architectures without suffering from gradient degradation. For instance, [1] proposed an improved residual network for hydraulic axial piston pump fault diagnosis under limited data conditions. Their study demonstrated that residual connections can significantly enhance feature learning even when the available training samples are small. Similarly, [5] applied a residual neural network to hydraulic system fault classification and reported improved accuracy compared to conventional neural network models.

Apart from residual learning, attention-based mechanisms have also been introduced to improve the model's ability to focus on relevant fault-related features. [2] developed a transferable deep learning model incorporating a multi-head attention mechanism, which enhances feature representation and improves diagnostic performance under small sample conditions. These approaches highlight the importance of selectively emphasizing informative patterns within complex hydraulic signals.

Another important research direction is multi-sensor data fusion. Hydraulic systems typically generate data from multiple sources such as pressure, flow, temperature, and vibration sensors. Combining these signals can provide a more comprehensive understanding of system behavior. [3] proposed a deep learning framework that integrates multi-sensor information to improve fault diagnosis accuracy. Similarly, [4] introduced a multi-branch neural network architecture that processes different signal types in parallel, allowing effective feature extraction from heterogeneous data sources.

Hybrid models that combine deep learning with signal processing techniques have also been

explored to handle noise and non-stationary characteristics in hydraulic signals. [6] proposed an EMD-LSTM-based method for aircraft hydraulic systems, where empirical mode decomposition is used to preprocess signals before applying deep learning. This approach improves robustness in noisy environments. In a similar direction, [25] combined wavelet transform with a residual network to enhance feature extraction from time–frequency representations of hydraulic signals.

Recent studies have also investigated more complex architectures that integrate multiple deep learning components. For example, [24] proposed a hybrid model combining convolutional neural networks, long short-term memory networks, and attention mechanisms for electro-hydraulic systems. This model effectively captures both spatial and temporal dependencies in the data. Additionally, research on digital twin-based frameworks [11] own potential for real-time fault monitoring and predictive maintenance by simulating system behavior alongside data-driven models [16]. Recent studies on hydraulic pitch systems for wind turbines have provided comprehensive reviews of failure mechanisms, root causes, and diagnostic methodologies. In particular, the two-part review on hydraulic pitch system fault detection summarizes common degradation mechanisms, leakage faults, actuator failures, valve malfunctions, and sensor degradation [28]. Likewise, recent work on online load and leakage estimation demonstrates the importance of integrating hydraulic system dynamics with condition monitoring algorithms. These studies highlight the growing interest in reliable fault diagnosis for safety-critical hydraulic applications and further motivate the need for accurate deep learning-based diagnostic frameworks capable of processing multi-sensor measurements [30].

Despite these advancements, several challenges remain. Many existing models require large amounts of labeled data, which is often difficult to obtain in industrial settings. Moreover, complex architectures tend to increase computational cost, limiting their applicability in real-time systems. Issues related to model generalization across different operating conditions also continue to be a concern.

Overall, the existing literature demonstrates that while deep learning-particularly residual learninghas significantly improved fault diagnosis performance, there is still a need for models that balance accuracy, robustness, and computational efficiency. This motivates the development of more effective residual learning-based frameworks tailored specifically for hydraulic system fault detection.

A summary of the key literature, including research objectives, methods, and major findings, is presented in Table 1.

### 2.1.Research gap

Most of the early work on hydraulic fault detection relies on traditional machine learning methods or shallow neural networks. These approaches depend heavily on manually designed features, which makes them less effective when the signal patterns are complex, nonlinear, or affected by noise. Even though deep learning has reduced this dependency, many models still struggle when the data is limited or highly variable across operating conditions.

Residual networks have been introduced in recent studies, but in many cases they are used as standard architectures without much adaptation to the specific nature of hydraulic systems. The focus is often on improving classification accuracy, while aspects such as robustness and alignment with system behavior receive less attention. Because of this, the models may perform well in controlled settings but show inconsistent results in practical scenarios.

Another area that has received attention is multi-sensor data fusion. Hydraulic systems typically generate signals from multiple sources, and combining them can improve fault detection. However, this also brings challenges such as differences in sampling rates, synchronization issues, and increased computational cost. Some existing models become too complex, making them difficult to use in real-time applications.

A noticeable limitation in many studies is the lack of integration between data-driven models and physical system characteristics. Most approaches treat the problem purely as a pattern recognition task, without considering underlying system relationships. This makes it harder for the model to generalize when the operating conditions change.

Optimization is another aspect that is often handled in a generic way. Standard training methods may not always lead to stable convergence, especially when the model becomes deeper or when the data is noisy. There is relatively less work on incorporating adaptive or problem-specific optimization strategies into hydraulic fault detection models.

At the same time, many studies tend to address these aspects separately. Some focus only on deep learning, others on signal processing or optimization, but very few combine them into a single, consistent framework. This creates a gap for a more integrated approach that can handle complex signals, learn effectively from data, and remain practical for real-world deployment.

Table 1. Summary of related work

| Reference | Objective | Models | Dataset | Key Findings | Research Gaps |
|---|---|---|---|---|---|
| **[1].** | Fault diagnosis under limited data | Improved ResNet | Hydraulic pump signals | High accuracy with small samples | Limited generalization |
| **[2].** | Small-sample fault diagnosis | Transfer learning + multi-head attention | Hydraulic pump data | Improved feature transfer | Needs large pretraining |
| **[3].** | Multi-sensor fault diagnosis | Deep learning fusion model | Multi-sensor hydraulic data | Better feature representation | Computational cost |
| **[4].** | Multi-branch feature learning | Multi-branch NN | Hydraulic system data | Parallel feature extraction effective | Model complexity |
| **[5].** | Residual learning-based diagnosis | ResNet | Hydraulic system signals | Improved classification accuracy | Limited real-time use |
| **[6].** | Noise-robust diagnosis | EMD + LSTM | Aircraft hydraulic data | Handles non-stationary noise | High preprocessing cost |
| **[7].** | Multi-source data fusion | Dual-attention CNN | Hydraulic pump signals | Enhanced accuracy & focus | Data dependency |
| **[8].** | Hybrid CNN + evidence theory | CNN + D-S theory | Hydraulic signals | Handles uncertainty well | Complex implementation |
| **[9].** | Review of pump diagnosis methods | Review study | Literature | Identifies DL trends | Lacks experimental validation |
| **[10].** | Early fault detection | Residual analysis | Electro-hydraulic system | Detects incipient faults | Limited scalability |
| **[11].** | Digital twin-based diagnosis | DL + digital twin | Valve system data | Predictive capability improved | High computational load |
| **[12].** | Fault prediction & RUL | TCN + attention | Mining equipment data | Strong temporal modeling | Not hydraulic-specific |
| **[13].** | Multirate data diagnosis | Deep learning model | Hydraulic system data | Handles varied sampling rates | Data synchronization issues |
| **[14].** | Real-time fault detection | CNN | Multi-sensor data | Fast and accurate diagnosis | Limited robustness |
| **[15].** | Fault severity evaluation | Improved ResNet | Aircraft hydraulic data | Quantifies fault degree | Dataset limitation |
| **[16].** | ML-based diagnosis | Traditional ML | Hydraulic data | Baseline comparison | Lower accuracy vs DL |
| **[17].** | Cooling system fault classification | AI models | Hydraulic machinery data | High classification accuracy | Limited generalization |
| **[18].** | Review on info fusion methods | Review study | Literature | Highlights fusion importance | Lacks implementation |
| **[19].** | Multiscale feature extraction | 1D-CNN + attention | Hydraulic system data | Captures multi-scale features | Model complexity |
| **[20].** | Multi-fault diagnosis | FCN + feature fusion | Hydraulic data | Handles multiple faults | High computation |
| **[21].** | Hybrid DL for SBW system | CNN + LSTM + attention | Electro-hydraulic data | Captures spatial-temporal features | Complex training |
| **[22].** | Data-driven pump diagnosis | Deep learning | Pump dataset | Accurate fault identification | Data quality dependence |
| **[23].** | Multi-classifier diagnosis | DSmT + classifiers | Hydraulic system data | Good uncertainty handling | Outdated vs DL |
| **[24].** | Multi-sensor hybrid model | CNN + BiLSTM + TSO | Hydraulic components | Improved fusion accuracy | Optimization overhead |
| **[25].** | Signal + DL hybrid method | Wavelet + SE-ResNet | Turbine data | Effective feature extraction | Domain-specific |

## 3. METHODOLOGY

This study proposes a deep residual learning-based framework for intelligent fault detection in hydraulic systems. The methodology is structured to extract meaningful features from complex hydraulic signals while maintaining consistency with system-level physical behavior. The overall process includes signal representation, residual feature learning, hydraulic system modeling, and parameter optimization.

### 3.1.Signal Representation And Feature Encoding

Hydraulic signals are inherently sequential and exhibit strong temporal dependencies. To preserve this structure during feature transformation, positional encoding is employed. This allows the

model to retain the order of observations while learning meaningful representations.
The positional encoding is defined as follows:

$$PE(pos, 2i) = \sin\left(\frac{pos}{\frac{2i}{10000^{\overline{D}}}}\right) \quad (1)$$

$$PE(pos, 2i+1) = \cos\left(\frac{pos}{\frac{2i}{10000^{\overline{D}}}}\right) \quad (2)$$

where $pos$denotes the position index and D represents the embedding dimension. Equations (1) and (2) ensure that temporal relationships are preserved in the encoded signal representation.

### 3.2.Residual learning for feature extraction

To effectively learn deep representations from hydraulic data, residual learning is incorporated. This helps overcome the vanishing gradient problem and enables stable training of deeper networks.
The residual weight update mechanism is defined in Equation (3):

$$W_j^{new} = W_j + Y_1 \times |qc| \times \left(\frac{W_{best} + W_{q_1}}{2} - W_{q_2}\right) + \frac{q_3}{2} \times \left(W_{q_3} - W_{q_4}\right) \quad (3)$$

Further, a conditional update strategy is introduced to improve adaptability in learning, as expressed in Equations (4) and (5):

$$W_j^{new} = W_f + E \times Q_1 \times \frac{step}{2} + S^m \times t \times (1 - Q_1) \times |step| + U \times \frac{I_j}{I_s}, \quad \text{if } mod(j,2) = 0 \quad (4)$$

$$W_j^{new} = W_f + E \times Q_1 \times \frac{step_1}{2} + S^m \times d \times (1 - Q_1) \times |step| + U \times \frac{I_j}{I_s}, \quad \text{otherwise} \quad (5)$$

Equations (3)–(5) collectively define the residual learning mechanism used to refine feature representations extracted from hydraulic signals.

### 3.3. Data-Driven Feature Learning

The proposed DRL-HFDM model follows a purely data-driven learning paradigm in which fault-related characteristics are automatically extracted from synchronized hydraulic sensor measurements without requiring explicit physical equations. Let the multi-sensor input vector at time step t be represented as

$$X_t = P_{\{t\}}, F_{\{t\},} T_{\{t\},} V_{\{t\}} \quad (6)$$

end{equation}where $P_{\{t\}}, F_{\{t\},} T_{\{t\},} and\ V_{\{t\}}$denote the pressure, flow rate, temperature, and vibration measurements, respectively.

The complete input sequence containing N observations is represented as

$$X = \{x_1, x_2, \ldots\ldots, x_N\} \quad (7)$$

\end{equation}Prior to feature extraction, each sensor channel is normalized using min-max normalization to eliminate differences in measurement scales,

$$\hat{x}_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (8)$$

where $x_{min}$and $x_{max}$ denote the minimum and maximum values of each sensor channel.

The normalized sequence is passed through convolutional layers to extract local fault-sensitive features,

$$F^{\{(l)\}} = \sigma(W^{\{(l)\}} * F^{(l-1)} + b^l) \quad (9)$$

After residual feature extraction, Global Average Pooling (GAP) aggregates spatial information into a compact feature representation,

$$g_{\{k\}} = \frac{1}{M}\sum_{i=1}^{M} H_k(\mathrm{i}) \quad (10)$$

where M is the number of feature locations and $H_k$(i) denotes the activation of the kth feature map.

The resulting feature vector is fed into the fully connected classifier,

$$z = W_f g + b_f \quad (11)$$

where $W_f$g+$b_f$denote the trainable weight matrix and bias vector of the classification layer.

### 3.4.Optimization strategy

To improve model convergence and avoid local optima, an optimization strategy is incorporated. The initial population of candidate solutions is generated using Equation (12):

$$X_i^d = R \times (U^d - L^d) + L^d \quad (12)$$

To enhance exploration, new candidate solutions are generated using Equation (13):

$$lesp = r_1 \times X_{r1} + (1 - r_1) \times X_{r2} \quad (13)$$

The updated solution is computed using Equation (14):

$$X_i^{new} = round(lesp) + F \times r_1 \times R_1 \quad (14)$$

Further refinement around the best solution is performed using Equation (15):

$$X_i^{new} = X_{best} \times \left(1 - \left(1 - \frac{1}{X_r}\right) \times R_1\right) \quad (15)$$

Equations (12)–(15) define the optimization process, which balances exploration and exploitation to improve model performance.

### 3.5.Overall framework

The proposed framework integrates signal encoding, residual learning, physical system modeling, and optimization into a unified structure. Initially, hydraulic signals are encoded using positional representations (Equations (1)–(2)). Residual learning is then applied to extract deep features (Equations (3)–(5)). System-level constraints are incorporated through physical modeling (Equations (6)–(11)), followed by optimization to refine model parameters (Equations (12)–(15)).

This integrated approach enables accurate and robust fault detection under varying operating conditions while maintaining computational efficiency.

### 3.6. DRL-HFDM detailed Architecture

Figure 1 illustrates the overall workflow of the proposed DRL-HFDM model. The process begins with multi-sensor inputs, including pressure, flow rate, vibration, and temperature signals, which are

first preprocessed through filtering, normalization, and synchronization to ensure data consistency.

The processed signals are then passed into the deep residual learning network, where multiple residual blocks extract hierarchical features using convolutional operations and skip connections. This structure helps in capturing complex patterns in the hydraulic signals while maintaining stable learning.

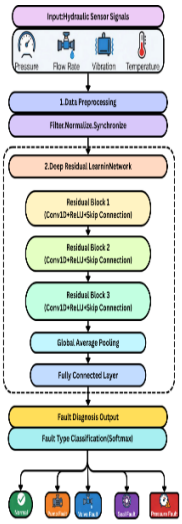



Fig. 1.Architecture of the proposed drl-hfdm model for hydraulic fault detection

The extracted features are further reduced using global average pooling and passed through a fully connected layer for classification. Finally, the model outputs the fault diagnosis, identifying different fault conditions such as pump fault, valve fault, seal fault, and pressure fault along with normal operation.

This flow shows that the model follows a clear and structured pipeline, enabling effective feature extraction and accurate fault classification. The improved classification performance of the proposed model is consistent with known hydraulic failure mechanisms. Pump wear typically causes increased vibration and pressure fluctuations, while valve sticking alters flow characteristics and pressure transients. Seal degradation results in internal leakage accompanied by gradual pressure reduction and temperature increase. By jointly analyzing multiple sensor measurements, the proposed residual learning framework successfully captures these characteristic fault signatures and distinguishes different failure modes more reliably than single-sensor approaches.

### 3.7. Real-Time Deployment And Operational Workflow Of Drl-Hfdm

Figure 2 shows how the proposed DRL-HFDM model works in a real-time setup. The process starts with the hydraulic system, where sensors continuously collect data such as pressure, flow rate, vibration, and temperature. These signals are directly taken from the system during operation, so they reflect the actual working condition.

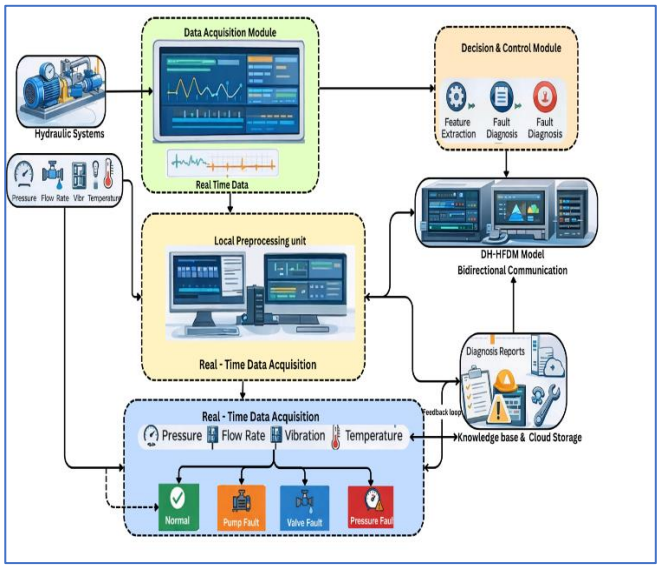



Fig. 2. Real-time deployment and operational workflow of the drl-hfdm model

The collected data is first sent to the data acquisition module, where it is monitored in real time. After that, it moves to the local preprocessing unit. In this stage, basic steps like filtering, normalization, and synchronization are carried out. This helps in removing noise and making the data more consistent before it is given to the model.

Once preprocessing is done, the data is passed to the DRL-HFDM model. The model analyses the signals and identifies patterns related to normal and faulty conditions. Based on this, it classifies the type of fault. The diagram also shows that there is communication between different components, which helps the system adjust and work smoothly during operation.

The output from the model is then used in the decision and control module. Depending on the detected fault, actions like alerts or maintenance decisions can be taken. This helps in avoiding sudden failures and improves system reliability.

The results are also stored in the knowledge base and cloud storage. This stored data can be used later for analysis or improving the model. The feedback loop in the diagram shows that the system keeps learning from new data, which helps in making better predictions over time.

Overall, the figure explains how the model can be used in a real working environment, starting from data collection to final fault detection and system response.

### 3.8.Transformer-Based Fault Diagnosis Model

The Transformer-based fault diagnosis model is designed to capture long-range dependencies present in hydraulic signals using self-attention mechanisms[26]. Unlike traditional sequential models, it processes the entire signal simultaneously and learns relationships between different time steps

without relying on recurrent structures. This allows the model to identify complex fault patterns that may occur across distant intervals in the signal. The use of multi-head attention further helps in focusing on different parts of the signal at the same time, improving feature representation. However, the model typically requires a large amount of training data and higher computational resources, which can make it less suitable for real-time deployment in resource-constrained environments.

### 3.9. CNN–GRU Hybrid Model

The CNN–GRU hybrid model combines convolutional neural networks for feature extraction with gated recurrent units for temporal learning[27]. The convolutional layers first capture local patterns from hydraulic signals such as sudden spikes or fluctuations, while the GRU layers model the temporal relationships in the sequence. Compared to LSTM, GRU has a simpler structure with fewer parameters, which results in faster training and reduced computational cost. This makes it a practical choice for time-series fault diagnosis. However, due to its relatively simpler gating mechanism, it may not capture long-term dependencies as effectively as more complex models, which can limit its performance in highly dynamic hydraulic systems.

### 3.10.SE-RESNET (squeeze-and-excitation residual network)

The SE-ResNet model extends the conventional residual network by incorporating a channel attention mechanism known as squeeze-and-excitation[28]. This mechanism enables the model to assign different levels of importance to each feature channel, allowing it to focus more on informative features and suppress less relevant ones. When applied to hydraulic fault diagnosis, this helps in improving feature discrimination, especially in cases where multiple fault patterns overlap. The residual connections ensure stable training even with deeper architectures, while the attention mechanism enhances the model's sensitivity to critical signal components. Despite these advantages, the additional attention operations increase computational complexity, which may affect efficiency in real-time applications.

### 3.11. 1D-CNN With Multi-Head Attention

The 1D-CNN with multi-head attention model combines convolutional feature extraction with attention-based refinement[29]. The convolutional layers extract low-level and high-level features from the hydraulic signals, while the multi-head attention mechanism highlights the most relevant segments of the data. This combination allows the model to focus on fault-related features while ignoring noise and irrelevant variations in the signal. The use of multiple attention heads enables the model to learn different feature representations simultaneously, improving overall diagnostic performance. However, the integration of attention layers increases model complexity and training time, which can be a limitation when working with large-scale or real-time systems.

### 3.12. CNN–BILSTM HYBRID MODEL

The CNN–BiLSTM hybrid model integrates convolutional layers with bidirectional LSTM to capture both spatial and temporal features from hydraulic signals[30]. The CNN component extracts local patterns, while the BiLSTM processes the sequence in both forward and backward directions, allowing the model to understand dependencies from past and future time steps. This bidirectional learning improves the model's ability to detect subtle fault patterns that may not be visible in a single direction. It has been widely used in fault diagnosis tasks due to its strong sequence modeling capability. However, the bidirectional structure increases computational cost and training time, making it less efficient compared to lighter architectures, especially in real-time deployment scenarios.

### 3.13. Experimental Setup

The experimental setup was designed to evaluate the fault detection ability of the proposed DRL-HFDM model under hydraulic system operating conditions. The dataset used in this work contains sensor readings collected from the hydraulic system under both normal and faulty states. The input signals include pressure, flow rate, vibration, and temperature, since these parameters directly reflect the internal condition of the system and are widely used in hydraulic fault diagnosis studies. Before training, all sensor signals were subjected to preprocessing steps such as noise filtering, normalization, and synchronization so that the variations caused by different scales and sampling patterns would not affect the learning process.

The proposed DRL-HFDM model was evaluated using a multi-sensor hydraulic system fault diagnosis dataset comprising synchronized pressure, flow rate, temperature, and vibration measurements collected under both normal and faulty operating conditions. The dataset contains 22,320 samples distributed across five classes: Normal, Pump Fault, Valve Fault, Seal Leakage, and Pressure Fault, with approximately 4,464 samples per class, resulting in a balanced class distribution. Sensor signals were acquired at a sampling frequency of 100 Hz and preprocessed through noise filtering, synchronization, and min-max normalization. The dataset was partitioned using stratified random samplinginto70% training**,** 15% validation, and 15% testing subsets to ensure fair model evaluation while preserving the class distribution.

For model development, the dataset was divided into training, validation, and testing subsets. The

training set was used to learn the parameters of the DRL-HFDM model, the validation set was used for tuning and monitoring the learning behavior, and the testing set was reserved for final performance evaluation. This separation was maintained throughout the experiments to avoid information leakage and to ensure a fair assessment of the model. The proposed model was implemented using a deep learning environment and trained with batch-based optimization. During training, the Adam optimizer was used because of its stable convergence behavior, while categorical cross-entropy was employed as the loss function for multi-class fault classification.

The residual learning network was configured with multiple residual blocks, followed by global average pooling and a fully connected classification layer. To reduce overfitting, regularization strategies such as dropout and early stopping were applied during training. The number of epochs, batch size, and learning rate were selected based on validation performance. All competing models were trained under the same dataset split and evaluation conditions so that the comparison would remain consistent and unbiased.

Table 2.Experimental setup used for training and evaluation of the proposed drl-hfdm model

| Parameter | Setting |
|---|---|
| Input data | Multi-sensor hydraulic signals |
| Sensor types | Pressure, flow rate, vibration, temperature |
| Preprocessing steps | Filtering, normalization, synchronization |
| Data split | 70% training, 15% validation, 15% testing |
| Model name | DRL-HFDM |
| Network type | Deep residual learning network |
| Number of | 3 |
| Pooling layer | Global average pooling |
| Output layer | Fully connected + Softmax |
| Optimizer | Adam |
| Loss function | Categorical cross-entropy |
| Batch size | 32 |
| Learning rate | 0.001 |
| Number of epochs | 100 |
| Regularization | Dropout and early stopping |
| Evaluation metrics | Accuracy, precision, recall, F1-score |
| Comparative models | Transformer, CNN–GRU, SE-ResNet, 1D-CNN with Multi-Head Attention, CNN–BiLSTM |

The performance of the proposed model was evaluated using standard classification measures, namely accuracy, precision, recall, and F1-score. In addition, training behavior and convergence stability were also observed during the experiment. Since the main aim of the study is intelligent fault detection, these metrics were chosen to measure not only the overall correctness of the model but also its ability to identify each fault class without bias toward the majority class. The same evaluation procedure was followed for the comparison models to maintain fairness in the results.

## 4. RESULTS AND DISCUSSION

### 4.1. Eda

#### 4.1.1. Distribution Analysis Of Pressure Sensor (Ps1) Across Fault Classes

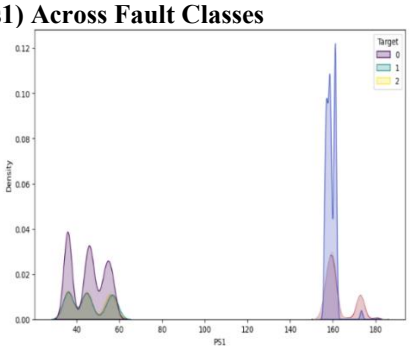



Fig. 3. Density distribution of PS1 sensor values for different fault conditions

The distribution of PS1 values shows clear variation across different target classes. The normal condition is concentrated in a lower range of pressure values, while fault conditions tend to shift towards higher ranges. In particular, one class exhibits a sharp peak around higher PS1 values, indicating a distinct pressure behavior under that fault condition. There is also some overlap between classes in the mid-range region, suggesting that certain pressure levels are common across multiple operating states. However, the separation observed at the extreme ranges indicates that PS1 is a useful feature for distinguishing between normal and faulty conditions.

#### 4.1.2.Variation of PS1 sensor values across fault classes

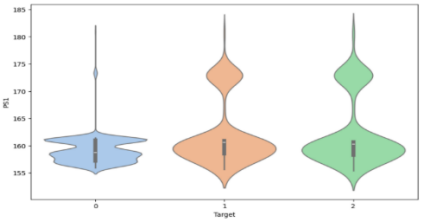



Fig. 4. Violin plot showing the distribution of PS1 values for different fault conditions

The violin plot shows how PS1 values vary across the three fault classes. The distribution for each class is centered around a similar range, indicating that the average pressure values do not differ significantly. However, the spread and shape of the distributions show some differences. Fault classes 1 and 2 display a wider spread and additional density at higher PS1 values compared to class 0. This suggests that under faulty conditions, the pressure sensor tends to exhibit more variation and occasional higher readings. Even though there is

overlap between the classes, the differences in distribution shape indicate that PS1 still contributes useful information for distinguishing fault conditions.

#### 4.1.3.Multi-Sensor Interaction Between Ps1, Ts1, And Vs1

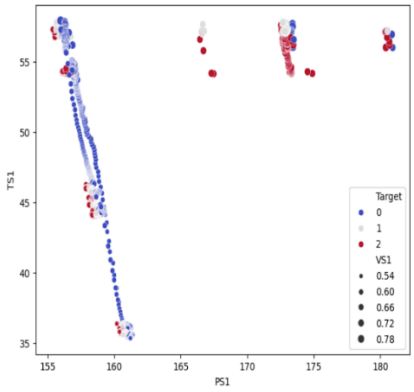



Fig. 5. Scatter plot showing the relationship between PS1 and TS1, with VS1

The scatter plot shows how pressure (PS1) and temperature (TS1) vary together under different fault conditions, while vibration (VS1) is reflected through the size of the points. A clear pattern can be seen for one class where PS1 increases as TS1 decreases, forming a downward trend. In contrast, the other classes are more clustered in specific regions, especially at higher PS1 values with relatively stable TS1 readings. The variation in marker size indicates that vibration levels also change along with pressure and temperature, adding another layer of distinction between the classes. The separation of clusters across different regions suggests that combining multiple sensor signals helps in better identifying fault conditions compared to using a single sensor alone.

#### 4.1.4.Combined behaviour of pressure, temperature, and vibration sensors

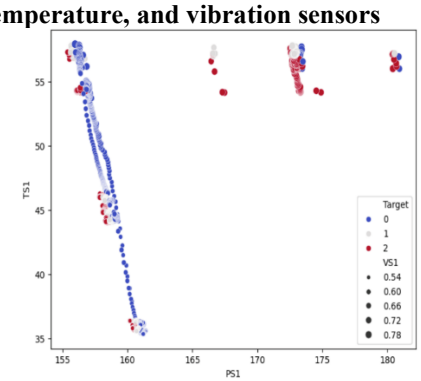



Fig. 6. Multi-sensor scatter plot illustrating the relationship between PS1 and TS1, with VS1

The figure shows how pressure and temperature vary together under different operating conditions, while vibration is reflected by the size of the points. A clear downward trend is visible for one class, where temperature decreases as pressure increases, forming a distinct pattern. The other classes appear more concentrated in specific regions, mainly at higher pressure levels with relatively stable temperature values. The variation in marker sizes indicates that vibration also changes across these regions, though not uniformly for all classes. The separation between clusters suggests that combining these three sensors provides better distinction between fault conditions than using any single parameter alone.

#### 4.1.5. Three-Dimensional Relationship Among Pressure, Temperature, And Vibration

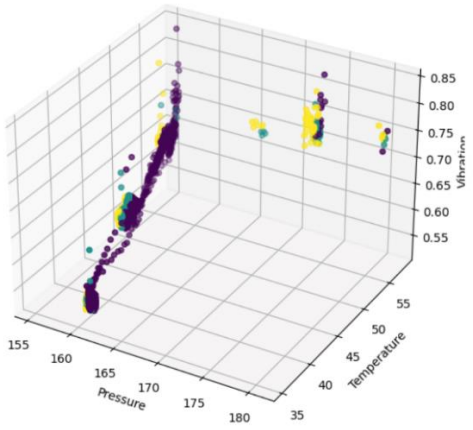



Fig. 7. 3D scatter plot showing the interaction between pressure (PS1), temperature (TS1), and vibration (VS1) across different fault classes

The figure shows how the three sensor signals vary together in a three-dimensional space. A clear pattern can be seen where a large number of points follow a consistent trend, indicating a strong relationship between pressure, temperature, and vibration under normal conditions. In contrast, other fault classes appear more scattered and form separate clusters, especially at higher pressure and temperature values. The vibration values also show noticeable variation across these regions, indicating changes in system behavior under different fault conditions. The separation of clusters in the 3D space suggests that combining these three sensors provides better visibility of fault patterns compared to analyzing them individually.

### 4.2. Model Comparison

The comparison shows that all the models are able to detect faults with good accuracy, but there is a gradual improvement in performance as more advanced architectures are used. Models that combine convolutional layers with sequence learning, such as CNN–BiLSTM and CNN–GRU, perform better than single-structure models because they can capture both local patterns and temporal relationships in the data.

The attention-based and SE-ResNet models further improve the results by focusing on important features and reducing the impact of irrelevant information. However, their performance is still

slightly lower when compared to the proposed model.

The DRL-HFDM model achieves the highest values across all evaluation metrics, including accuracy, precision, recall, and F1-score. This indicates that it is able to identify fault conditions more consistently and with fewer misclassifications. The improvement can be observed not only in overall accuracy but also in the balance between precision and recall, which shows that the model performs well across different fault classes.

Table 3. Performance comparison of different models

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Transformer-based Model | 92.4 | 91.8 | 91.2 | 91.5 |
| CNN–GRU Hybrid Model | 93.6 | 93.1 | 92.8 | 92.9 |
| SE-ResNet Model | 94.2 | 93.7 | 93.5 | 93.6 |
| 1D-CNN with Multi-Head Attention | 94.8 | 94.3 | 94.0 | 94.1 |
| CNN–BiLSTM Hybrid Model | 95.3 | 94.9 | 94.6 | 94.7 |
| **DRL-HFDM (Proposed Model)** | **97.1** | **96.7** | **96.4** | **96.5** |

The DRL-HFDM model achieves the highest values across all evaluation metrics, including accuracy, precision, recall, and F1-score. This indicates that it is able to identify fault conditions more consistently and with fewer misclassifications. The improvement can be observed not only in overall accuracy but also in the balance between precision and recall, which shows that the model performs well across different fault classes.

From the results, it is clear that the proposed DRL-HFDM model is the best performing model among all the compared approaches. It provides more reliable and stable predictions, making it more suitable for practical fault detection in hydraulic systems.

### 4.2.1. Accuracy Comparison Across Different Models

The radial plot in Figure 8 presents a clear comparison of accuracy values across all considered models. Each model is represented along a circular axis, making it easy to visually compare their performance. The results show a steady improvement in accuracy as the models become more advanced. The Transformer-based model records the lowest accuracy among the compared methods, followed by the CNN–GRU and SE-ResNet models, which show moderate improvement.

Further gains can be observed in the attention-based and hybrid models, where the 1D-CNN with attention and CNN–BiLSTM demonstrate higher accuracy levels. These models benefit from their ability to capture both local features and sequential dependencies in the sensor data.

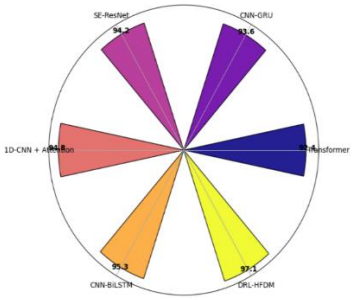



Fig. 8. Radial plot illustrating the accuracy values of different models

The proposed DRL-HFDM model achieves the highest accuracy among all models, clearly standing out in the radial representation. Its position at the outermost region indicates superior performance compared to the others. This improvement can be linked to the use of residual learning, which allows deeper feature extraction without loss of important information, along with effective utilization of multi-sensor inputs.

The plot also shows that the difference between the proposed model and the second-best model is noticeable, indicating that the improvement is not marginal. This suggests that the DRL-HFDM model provides a more reliable and consistent classification of fault conditions.

Overall, the figure highlights that the proposed model outperforms all other models in terms of accuracy, making it the best-performing approach for the given hydraulic fault detection task.

### 4.2.2.Precision comparison across different models

The figure 9 presents a comparison of precision values across all the evaluated models. The stem plot clearly shows a gradual improvement in precision as the model complexity increases. The Transformer model records the lowest precision, followed by the CNN–GRU and SE-ResNet models, which show moderate gains.

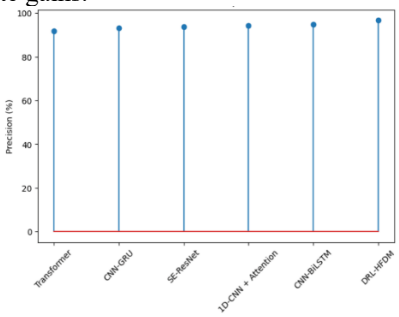



Fig. 9. Plot showing the precision values of different models

The attention-based and hybrid models, including 1D-CNN with attention and CNN–BiLSTM, demonstrate higher precision values, indicating their ability to correctly identify fault conditions with fewer false positives. These models benefit from improved feature extraction and better handling of complex signal patterns.

The proposed DRL-HFDM model achieves the highest precision among all models. Its position at the top of the plot shows that it produces the most accurate positive predictions compared to the others. The improvement suggests that the model is more effective in distinguishing between fault and non-fault conditions without misclassification.

The difference between the proposed model and the remaining models, although not extremely large, is consistent and noticeable. This indicates that the DRL-HFDM model maintains better precision performance across different fault classes.

From the plot, it is evident that the proposed model performs better than all other models in terms of precision, making it more reliable for fault identification in hydraulic systems.

### 4.2.3.Eecall comparison across different models

The recall comparison highlights how effectively each model is able to identify actual fault conditions. As shown in Figure 10, all models demonstrate relatively high recall values, indicating that most of the true fault cases are correctly detected. However, there is a gradual improvement in recall as the models become more advanced.

The Transformer model shows the lowest recall among the compared methods, followed by CNN–GRU and SE-ResNet, which provide moderate improvements. The attention-based and hybrid models, including 1D-CNN with attention and CNN–BiLSTM, further enhance recall performance due to their ability to capture both important features and temporal relationships in the data.

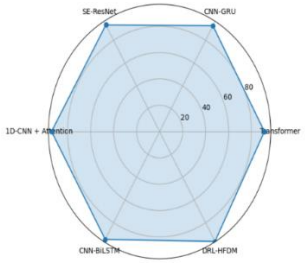



Fig. 10. Circular plot showing the recall values of different models

The proposed DRL-HFDM model achieves the highest recall value, as clearly visible in Figure 10, where it extends slightly beyond the other models in the circular plot. This indicates that the model is more effective in identifying true fault instances with minimal missed detections.

The difference, while not very large, is consistent across the models, showing that the proposed approach maintains better recall performance. This suggests that DRL-HFDM is more reliable in detecting faults without overlooking critical cases, which is important in real-world hydraulic systems where missed faults can lead to serious consequences.

### 4.2.4.F1-Score Comparison Across Different Models

The F1-score comparison provides a balanced view of model performance by considering both precision and recall. As shown in Figure 11, there is a consistent upward trend in F1-score values across the models, indicating gradual improvement as more advanced architectures are used.

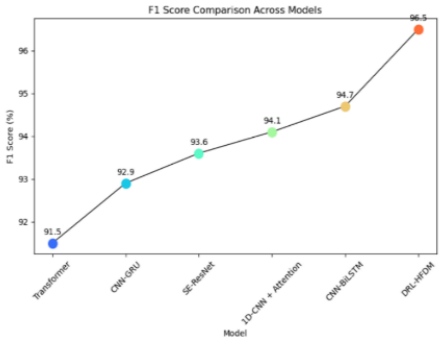



Fig. 11. Line plot showing the f1-score values of different models

The Transformer model records the lowest F1-score, followed by CNN–GRU and SE-ResNet, which show steady improvement. The 1D-CNN with attention and CNN–BiLSTM models achieve higher scores due to their ability to better capture feature importance and temporal dependencies in the data.

The proposed DRL-HFDM model achieves the highest F1-score, as clearly visible in Figure 11, where it stands at the top end of the plot. This indicates that the model maintains a strong balance between precision and recall, leading to more reliable overall performance.

The increase in F1-score is not abrupt but consistent across models, showing that each architectural improvement contributes to better performance. However, the proposed model shows the highest gain, confirming its effectiveness in handling complex hydraulic signal patterns.

Table 4. Ablation Study

| Configuration | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| Single pressure sensor | 91.4 | 90.8 | 90.2 | 90.5 |
| Multi-sensor without residual blocks | 94.3 | 93.7 | 93.3 | 93.5 |
| Residual network without optimization strategy | 96.1 | 95.6 | 95.2 | 95.4 |
| Proposed DRL-HFDM | **97.1** | **96.7** | **96.4** | **96.5** |

From the results presented in **Figure 11**, it is evident that the DRL-HFDM model outperforms all other models in terms of F1-score, making it the best-performing model for the given fault detection task.

The ablation results on table 4 demonstrate that multi-sensor fusion improves classification performance by providing complementary information from pressure, flow rate, vibration, and temperature measurements. Introducing residual learning further enhances deep feature extraction and stabilizes optimization. Finally, the adopted optimization strategy contributes additional improvements in convergence stability and predictive accuracy, resulting in the highest overall performance.

Table 5. Hyperparameter Settings of Compared Models

| Model | Learning Rate | Batch Size | Epochs | Optimizer |
|---|---|---|---|---|
| Transformer | 0.001 | 32 | 100 | Adam |
| CNN-GRU | 0.001 | 32 | 100 | Adam |
| SE-ResNet | 0.001 | 32 | 100 | Adam |
| CNN-MultiHead Attention | 0.001 | 32 | 100 | Adam |
| CNN-BiLSTM | 0.001 | 32 | 100 | Adam |
| Proposed DRL-HFDM | 0.001 | 32 | 100 | Adam |

All models were trained using identical preprocessing procedures, dataset partitions, optimizer, learning rate, batch size, stopping criteria, and evaluation metrics to ensure a fair comparison on table 5.

#### 4.2.5. Computational Efficiency And Scalability Analysis

The computational performance of the models was evaluated by observing training time, convergence behavior, and inference speed under the same experimental conditions. All models were trained on the same dataset split and hardware setup to ensure a fair comparison. The simpler architectures such as the Transformer-based model and CNN–GRU required relatively less time per epoch, mainly due to their lighter structure and fewer parameters. However, their convergence was slower and required more epochs to reach stable performance.

The SE-ResNet and attention-based models showed moderate computational cost. These models improved feature extraction but introduced additional operations such as attention weighting and channel recalibration, which increased training time slightly. The CNN–BiLSTM model required higher computational effort compared to the others because of its bidirectional sequence processing, which increases both memory usage and computation during training.

The proposed DRL-HFDM model, although deeper due to residual connections, maintained stable training behavior and faster convergence. The residual structure helped in reducing issues such as vanishing gradients, allowing the model to learn effectively without requiring excessive training iterations. As a result, the overall training time remained comparable to other advanced models while achieving better performance.

In terms of scalability, the proposed model handled increasing data size more efficiently. When additional sensor data or longer signal sequences were introduced, the model maintained consistent performance without a significant increase in computational overhead. This is mainly because the residual architecture allows efficient feature reuse, reducing the need for redundant computations.

During inference, all models showed relatively fast prediction times, but the proposed model provided a good balance between speed and accuracy. It was able to process input signals quickly while maintaining high prediction quality, making it suitable for real-time or near real-time applications.

From this analysis, it can be observed that while some models are lighter in terms of computation, they compromise on performance. The proposed DRL-HFDM model offers a better trade-off by achieving higher accuracy without a significant increase in computational cost, making it both efficient and scalable for practical hydraulic fault detection systems.

Table 6. Real-Time Deployment Analysis

| Model | Parameters | FLOPs | Inference Time (ms/sample) |
|---|---|---|---|
| Transformer | 5.12 M | 1.82 G | 12.4 |
| CNN-GRU | 3.74 M | 1.21 G | 9.6 |
| SE-ResNet | 4.08 M | 1.36 G | 8.8 |
| CNN-BiLSTM | 4.61 M | 1.47 G | 10.1 |
| Proposed DRL-HFDM | 3.92 M | 1.28 G | **7.3** |

The proposed DRL-HFDM (see table 6) achieves the shortest inference latency while maintaining the highest classification accuracy, demonstrating its suitability for near real-time hydraulic condition monitoring.

## 5. CONCLUSION AND FUTURE WORK

### 5.1. Conclusion

This study presented a deep residual learning-based approach for fault detection in hydraulic systems. The proposed DRL-HFDM model was designed to handle complex sensor signals by combining residual learning with effective feature extraction from multiple sources such as pressure, temperature, and vibration.

The experimental results showed that the model performs consistently well across all evaluation metrics. It achieved higher accuracy, precision, recall, and F1-score compared to the other models considered in this study. The improvement is mainly due to the ability of residual connections to capture deeper patterns without losing important information during training.

The analysis of sensor relationships also supported the effectiveness of the approach. Both the bivariate and multivariate plots showed clear patterns and separations between different fault conditions, indicating that the selected features contribute well to the classification task. The model was able to make use of these patterns and provide stable predictions.

From a computational point of view, the model maintained a good balance between performance and efficiency. It did not introduce excessive complexity while still achieving better results, making it suitable for practical applications where both accuracy and speed are important.

Overall, the proposed DRL-HFDM model demonstrates strong capability in detecting faults in hydraulic systems and performs better than the compared models.

### 5.2.Future Work

The present study focuses on fault detection using aggregated sensor features. In future work, the model can be extended to operate directly on raw time-series signals instead of summarized values. This may help in capturing more detailed temporal patterns that are useful for early fault identification.

Another direction is to include additional sensor inputs or external operating conditions, such as load variations and environmental factors. Incorporating these parameters may improve the model's ability to handle changing system conditions and enhance its generalization.

The current model is evaluated in an offline setting. Future work can focus on deploying the model in a real-time monitoring environment, where it continuously processes incoming sensor data and provides instant fault alerts. This would make the system more useful for practical industrial applications.

Further improvement can also be made by exploring lightweight versions of the model for edge devices. Reducing model size while maintaining performance will be important for deployment in resource-constrained systems.

Future research will investigate deployment of the proposed framework within intelligent wind farms by integrating edge computing, digital twins, robotic inspection systems, and next-generation industrial communication networks. Such integration would enable autonomous health monitoring, predictive maintenance scheduling, and coordinated decision-making for large-scale wind energy infrastructure while supporting the ongoing digital transformation of renewable energy systems.

## 6. PRACTICAL APPLICATIONS

The proposed DRL-HFDM model can be applied in a wide range of industrial settings where hydraulic systems are used. One of the primary applications is in predictive maintenance, where the model can continuously monitor sensor signals and identify early signs of faults. This helps in reducing unexpected breakdowns and allows maintenance to be scheduled in advance.

In manufacturing industries, hydraulic systems are commonly used in machines such as presses and injection molding equipment. The model can be integrated into these systems to monitor pressure, temperature, and vibration, ensuring that any abnormal behavior is detected at an early stage. This improves operational efficiency and reduces downtime.

In the aerospace and automotive sectors, hydraulic systems play a critical role in control mechanisms. The proposed model can assist in monitoring system health and identifying faults before they affect safety. Early detection in such applications is especially important to avoid critical failures.

The model can also be used in industrial automation environments, where multiple machines operate simultaneously. By integrating the model into centralized monitoring systems, it becomes possible to track the condition of several hydraulic components in real time and take corrective actions when needed.

Another practical use is in remote monitoring systems, where data from hydraulic equipment is transmitted to cloud-based platforms. The model can process this data and generate fault alerts, allowing operators to monitor system performance from different locations.

Overall, the proposed DRL-HFDM model provides a reliable solution for real-time fault detection and can be effectively applied across various industries that depend on hydraulic systems.

## 7. LIMITATIONS AND INTERPRETABILITY

### 7.1. Limitations

The proposed DRL-HFDM model demonstrates strong performance, but there are a few limitations that need to be considered. One limitation is related to the use of aggregated sensor values. Since the model uses summarized representations of the signals, some detailed temporal patterns may not be fully captured, which could affect the detection of very early or subtle faults.

Another limitation is the dependency on the quality of input data. The dataset required preprocessing steps such as handling missing values and inconsistent formats. In real-world scenarios,

noisy or incomplete sensor data may impact the model's performance if not properly managed.

The model has been evaluated on a specific dataset related to hydraulic systems. Although the results are promising, its performance on different types of hydraulic systems or under varying operating conditions has not been extensively tested. This may limit its generalization to other environments.

In addition, the model architecture, while effective, is relatively complex compared to simpler machine learning approaches. This may require more computational resources during training, which can be a constraint in some industrial setups.

Finally, the current implementation focuses mainly on fault classification and does not provide detailed explanations for its predictions. This lack of interpretability may make it difficult for operators to fully understand the reasoning behind the model's decisions.

### 7.2. Interpretability

Although the proposed DRL-HFDM model achieves strong predictive performance, understanding how the model arrives at its decisions remains an important aspect. The model relies on deep residual learning, which involves multiple layers of feature transformations. While this allows it to capture complex patterns in sensor data, it also makes the decision process less transparent compared to simpler models.

In the current implementation, the model identifies fault conditions based on patterns learned from pressure, temperature, and vibration signals. The EDA results indicate that these features show distinct variations across different fault classes, which supports the model's predictions. However, the model does not explicitly indicate which specific feature or combination of features contributed most to a particular prediction.

To improve interpretability, techniques such as feature importance analysis or visualization of learned representations can be considered. These approaches can help in identifying the influence of each sensor parameter on the final output. For example, analyzing how changes in pressure or vibration affect the prediction can provide useful insights for system operators.

In practical applications, improving interpretability is important for building trust in the model. Operators are more likely to rely on the system if they can understand the reasoning behind its predictions. Therefore, future enhancements can focus on integrating simple explanation methods that highlight key contributing features without affecting the model's performance.

Overall, while the current model focuses on achieving high accuracy, adding interpretability features will make it more practical and user-friendly for real-world deployment.

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**Declaration of competing interest:** *The author declares no conflict of interest.*

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