A REVIEW OF MACHINE LEARNING FOR CAVITATION INTENSITY RECOGNITION IN COMPLEX INDUSTRIAL SYSTEMS

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ABSTRACT

Cavitation intensity recognition (CIR) is a critical technology for detecting and evaluating cavitation phenomena in hydraulic machinery, with significant implications for operational safety, performance optimization, and maintenance cost reduction in complex industrial systems. Despite substantial research progress, a comprehensive review that systematically traces the development trajectory and provides explicit guidance for future research is still lacking. To bridge this gap, this paper presents a thorough review and analysis of hundreds of publications on intelligent CIR across various types of mechanical equipment from 2002 to 2025, summarizing its technological evolution and offering insights for future development. The early stages are dominated by traditional machine learning approaches that relied on manually engineered features under the guidance of domain expert knowledge. The advent of deep learning has driven the development of end-to-end models capable of automatically extracting features from multi-source signals, thereby significantly improving recognition performance and robustness. Recently, physical informed diagnostic models have been proposed to embed domain knowledge into deep learning models, which can enhance interpretability and cross-condition generalization. In the future, transfer learning, multi-modal fusion, lightweight network architectures, and the deployment of industrial agents are expected to propel CIR technology into a new stage, addressing challenges in multi-source data acquisition, standardized evaluation, and industrial implementation. The paper aims to systematically outline the evolution of CIR technology and highlight the emerging trend of integrating deep learning with physical knowledge. This provides a significant reference for researchers and practitioners in the field of intelligent cavitation diagnosis in complex industrial systems.

***K*eywords** Cavitation Detection · Cavitation Intensity Recognition · Complex Industrial System · Machine Learning · Deep Learning · Physical informed Deep Learning

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1 Introduction

Cavitation intensity recognition (CIR) is a critical technology for quantitatively evaluating cavitation phenomena occurring during the operation of hydraulic machinery [1]. Cavitation not only generates intense noise and vibration, but can also cause erosion on equipment component surfaces, performance degradation and structural failure, posing severe threats to the safety, stability and cost-effectiveness of industrial systems [2]. The high performance of CIR enables timely implementation of control measures, optimization of operating conditions, extension of equipment service lift and reduction of maintenance and downtime costs. Therefore, CIR holds significant engineering importance and practical relevance across sectors including energy, shipping, aerospace and chemical industrial, where pumps, turbines, propellers and valves serve as critical components [3]. With the advancement of sensing technology and the improvement of data acquisition capabilities, multi-source signals (e.g. acoustic, vibration, pressure, high-speed imaging, etc.) provide abundant diagnostic information for CIR, which has driven increasing attention from both academic and industry over the past two decades.

Intelligent cavitation intensity recognition (ICIR) represents a methodology that applies machine learning and deep learning from modern artificial intelligence techniques to cavitation intensity recognition [4]. Unlike traditional diagnostic approaches reliant on manual feature extraction and expert experience, ICIR can adaptively learn from complex multi-source sensor data. It can automatically capture cavitation features and establish a mapping between signals and cavitation intensity, which significantly reduces dependence on human intervention [5]. Firstly, it can process multi-modal information, enabling comprehensive cross-signal-type analysis and improving diagnostic performance and robustness. Secondly, it holds the capability to handle non-linear, multi-scale and high-noise signals, adapting to recognition requirements across various equipment types and operating condition. Thirdly, it achieves an automated workflow from raw data to recognition results through an end-to-end model, reducing diagnostic time and enhancing real-time monitoring capabilities. Fourthly, it can incorporate physical knowledge embedding and constraint loss methods to improve model interpretability and cross-condition generalization, which provides technical support for sustainable monitoring and predictive maintenance in industrial scenarios.

In recent years, ICIR has attracted increasing attention from both academic and industry, a trend closely related to the rapid development of machine learning technologies. To gain a comprehensive understanding of the technological evolution and research dynamics in this field, we have conducted a systematic statistical analysis of several hundred relevant publications from 2002 to 2025, as shown in Figure 1. This analysis aims to reveal the principal technical characteristics and developmental trends of each stage, which provides a basis for the division of subsequent research phases. Based on the observed changes in publication with technological advancement characteristics, we roughly divide the research of CIR into three periods as follows.

In the past, traditional machine learning (TML) methods served as the primary technical approach in CIR. These methods typically relied on manually engineered features extracted from acoustic, vibration or pressure signals by domain experts. These features are classified using classical algorithms such as support vector machines (SVM) [6], decision trees (DT) [7], artificial neural networks (ANN) [8], k-Nearest Neighbours (KNN) [9] and expert systems (ES) [10]. This stage of development reduced reliance on purely manual judgement, but feature construction remains time-consuming and labor-intensive and heavily dependent on expert experience. This leads to limited generalization capabilities across different operating conditions.

In the present, the rise of deep learning has driven ICIR into the era of end-to-end modeling. The deep learning models can automatically capture cavitation features directly from multi-source raw signals (e.g. acoustic, vibration, pressure, high-speed imaging, etc.) and also perform multi-modal information fusion to enhance recognition performance and robustness. The application of deep belief networks (DBN) [11], convolutional neural networks (CNN) [12], residual neural networks (ResNet) [13], dense convolutional networks (DenseNet) [14], MobileNet [15], ShuffleNet [16], recurrent neural networks (RNN) [17], long short-term memory (LSTM) [18], gated recurrent neural networks (GRU) [19] and Transformer [20] architectures has significantly improved the real-time performance and stability of CIR under complex operating conditions.

In the future, the development of ICIR will depend on standardized high-quality multi-source data acquisition and the design of physical informed deep learning diagnostic models. Through incorporating physical mechanisms, physical knowledge embedding and physical constraint losses into end-to-end data-driven deep learning, which can enhance the physical consistency of the model [21]. This approach not only helps improve the model's generalization capabilities under small-sample, high-noise and cross-operating conditions, but also significantly enhances the interpretability and engineering credibility of the diagnostic results [22, 23]. Compared to purely data-driven methods, physical-informed diagnostic models can better capture the non-linear, multi-scale characteristics of cavitation processes, ensuring diagnostic outputs are closely aligned with practical physical mechanisms [24]. In addition, in future industrial applications, the combination of real-time data acquisition by the industrial internet of things and edge computing

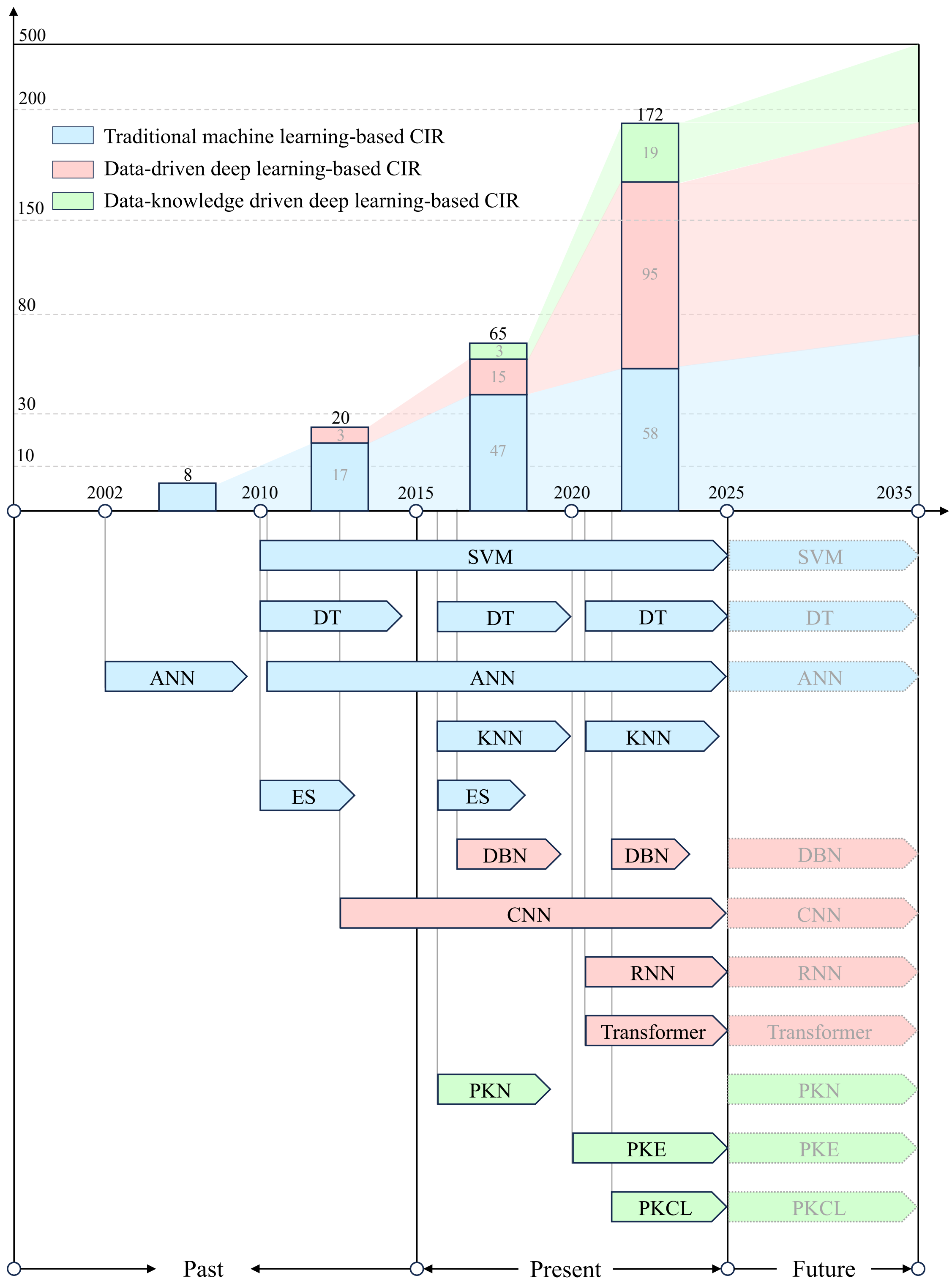

Figure 1: Development path and significant milestones of cavitation intensity recognition using machine learning.

deployment will enable physical informed deep learning diagnostic models to provide robust support for ICIR across equipment and operating conditions [25, 26].

To summarize the research of CIR, Wu at al. [1] discussed various methods for characterizing cavitation intensity and emphasizes three acoustic approaches. Liu et al. [27] analyzed pump cavitation detection methods based various signals and discussed future trends with intelligent algorithms and advanced sensing. Adil et al. [28] examined experimental methods and control systems for diagnosing and managing cavitation in centrifugal pumps, and proposed future improvements using more sensors, advanced data processing and artificial intelligence for early detection to enhance reliability and extend service life. Fernández et al. [29] outlined acoustic emission techniques for cavitation and fracture detection in hydraulic turbines and emphasized artificial intelligent as a key future direction for condition monitoring. Mousmoulis et al. [30] discussed cavitation monitoring tools for centrifugal pumps and advocated for developing reliable, low-cost and easy-to-install multi-sensor setups. Folden et al. [31] categorized cavitation models, analyzed key examples and outlined future improvements in flow simulation. Existing reviews on CIR have the following shortcomings. Firstly, the previous reviews just focus on a single technical approach or specific equipment type (e.g. pumps, turbines, acoustic detection, modeling methods, etc.) and lacks a systematic and integrated framework across different methods and devices, which makes it difficult to comprehensively compare their feasibility and cost-effectiveness. Secondly, these reviews typically cover only specific stage of CIR development, lacking a systematic overview that integrates past, present and future progress. Thirdly, the current reviews generally do not provide a roadmap for the future development of CIR, while potential research trends over the next five to ten years are of great interest to review readers. Fourthly, the present reviews provide limited coverage of emerging technologies such as deep learning and physical informed deep learning.

In order to overcome the above shortcomings, this paper systematically examines hundreds of studies across various hydraulic machinery from 2002 to 2025 and outlines a technological roadmap for this field. The contributions of this review are summarized as follows:

- The development of CIR is organized into three stages: past traditional machine learning, present deep learning and future physical informed deep learning, which helps systematically trace the technological evolution, clarify the key characteristics of each stage and provide guidance for future research directions.
- A future roadmap for CIR is proposed, highlighting physical-informed diagnostic models, multi-modal fusion, lightweight network architectures and industrial agents deployment as promising directions to overcome challenges in multi-source data acquisition, standardized evaluation and industrial implementation.
- A systemic view of CIR's technological evolution is presented and the trend of integrating deep learning with physical knowledge is emphasized, providing a valuable reference for intelligent cavitation diagnosis in complex industrial systems.

The rest of this review is organized as follows. Section 2 examines the past development of CIR, focusing on the applications of traditional machine learning theories. Section 3 reviews the applications of deep learning theories, representing the present period in the development of CIR. Section 4 argues applications of physical informed deep learning to CIR. In Section 5, a roadmap is outlined in conjunction with the challenges of CIR. Conclusions are provided in Section 6.

2 Traditional Machine Learning

Traditionally, cavitation intensity recognition (CIR) has primarily relied on operators' experience-based judgment of equipment operating conditions and on-site inspections [27, 30]. It not only increase maintenance workload but also affects the performance and consistency of diagnostic results. In recent years, with the continuous development of sensor technology and signal processing methods, researchers have gradually introduced traditional machine learning (TML) into CIR tasks, achieving automated prediction and recognition of cavitation states [32, 33]. A typical TML-based CIR includes four key steps: data acquisition, feature extraction, feature selection and intelligent intensity recognition [34, 35], see Figure 2. Each step will be discussed in the following subsections.

2.1 Data Acquisition

During the data acquisition phase, sensors are typically installed at critical locations on equipment (e.g. valves [36, 37], pipes [38, 39], pumps [40, 41], turbines [42, 43] and propellers [44, 45]) to enable continuous monitoring of operational conditions. Researchers employ various types of sensors to effectively capture the formation, development and associated physical changes of cavitation bubbles. Different types of sensors have their own advantages in terms of adaptability, sensitivity, resolution and anti-interference capability [30, 46], see Table 1. In general, pumps, valves,

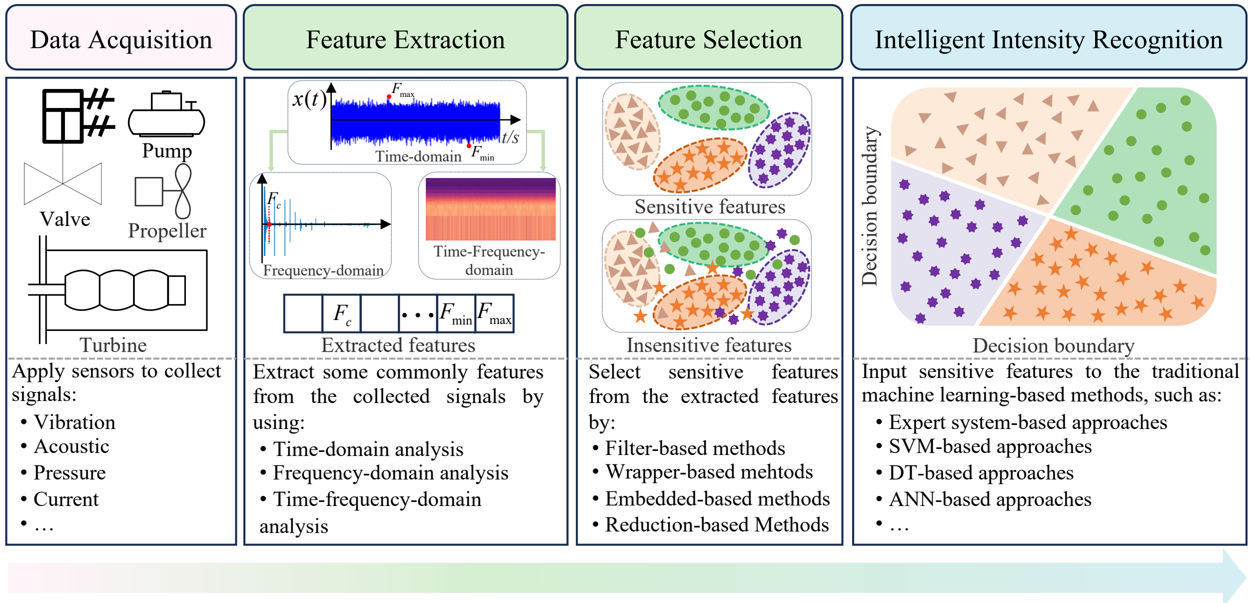

Figure 2: Diagnosis procedure of cavitation intensity recognition using traditional machine learning methods, which consists of data acquisition, feature extraction, feature selection and intelligent intensity recognition.

pipes and turbines commonly utilize vibration, acoustic and pressure sensors [47, 48, 49, 50, 51, 52], while propellers mainly use acoustic, pressure, current and high-speed sensors [53, 54]. By appropriately selecting and integrating multi-source sensor data, the performance and robustness of CIR can be significantly improved.

Table 1: Comparison of different sensors in data acquisition stage of cavitation intensity recognition.

Type	Principle	Characteristics
Ultrasonic Sensor	Analyzes variations in high-frequency	High resolution, sensitive to medium
High-speed Camera	Captures bubble flashing frequency	High temporal resolution, requires transparent medium, high cost
Energy Sensor	Measurement of energy changes	Quantitative, requires high-precision devices, high cost
Pressure Sensor	Detects local pressure pulsations	High sensitivity, real-time, vulnerable to corrosion and impact
Vibration Sensor	Monitors surface micro-vibrations	Flexible installation, low cost, source interference possible
Acoustic Sensor	Monitors sound wave changes	Remote monitoring, strong penetration, needs noise suppression

2.2 Feature Extraction

Feature extraction serves as a crucial bridge between raw sensor signals and TML models in CIR. By analysing the time-domain, frequency-domain and time-frequency-domain characteristics of the signals, multi-dimensional features that effectively represent the cavitation state can be extracted [55, 56, 57], as detailed below.

- Time-domain features: These are statistical quantities directly derived from the raw signal, including mean, variance, kurtosis, skewness, maximum value, minimum value, shape factor, peak factor, clearance factor, impulse factor, etc., reflecting the overall fluctuation characteristics of the signal [58, 59].
- Frequency-domain features: These are obtained from the frequency spectrum, including mean frequency, frequency center, frequency standard deviation, root mean square frequency, spectral entropy, energy spectral density, etc., which help capture frequency variations caused by cavitation [60].
- Time-frequency-domain features: These are suitable for non-stationary signal analysis, common methods include wavelet transform, wavelet packet transform, short-time Fourier transform and empirical model decomposition [61, 62, 63]. These approaches enable the characteristics of the dynamic evolution of cavitation across different time scales.

2.3 Feature Selection

Feature selection aims to filter out a discriminative and sensitive feature subset from high-dimensional features, reducing computational complexity, alleviating the dimension diaster and improving recognition performance [64, 65]. For CIR task, commonly used feature selection methods include filter-based, wrapper-based, embedded-based and reduction-based approaches, each of which has its own advantages and is suitable for different data scenarios and modeling requirements.

2.3.1 Filter-based Methods

Filter-based methods evaluate the correlation or statistical properties between each feature and the target variable, performing feature selection independently before the model training [66]. The following briefly introduces several commonly used filters.

- Variance threshold [67]: Remove features with low variance and low information content to enhance generalization ability of the model.
- Correlation coefficient analysis [68]: Calculate the linear or non-linear correlation between features and target variable (e.g. Pearson, Spearman or Kendall coefficients, etc.)
- Mutual information [69]: Measure the non-linear dependency between features and target variable, which is suitable for feature selection under complex distribution structures.
- Distance Evaluation [70]: Based on the principle of minimizing intra-class distance and maximizing inter-class distance, features with strong class discrimination capabilities are selected.
- Information gain and gain ratio [71]: Evaluate the effective amount of information carried by a feature. Features with higher information gain and gain ratio are generally more advantageous in enhancing the performance of diagnostic models.
- Minimum redundancy maximum relevance [72]: Select the most representative feature subset by maximizing the relevance between features and the target variable and minimizing redundancy among features.
- Relevant features [73]: Construct relevance metrics to evaluate the sensitivity of features to the target variable, and then select key features that are highly correlated with the target variable and exhibit significant class discrimination capabilities.
- Chi-square test [74]: Evaluate the independence between features and the target variable to determine the most relevant and sensitive features for the diagnostic model.

2.3.2 Wrapper-based Methods

Wrapper-based methods select optimal feature subsets by relying on the performance of TML models. The core idea of these methods is to convert the feature selection issue into a feature subset search task, i.e. guiding the selection of the feature subset based on the model's performance [65]. The following are common wrapper-based methods.

- Sequential selection [75]: Features are gradually added or remove features via forward selection or backward elimination to optimize model performance, which is suitable for high-dimensional feature spaces.
- Recursive feature elimination [76]: Iteratively remove features with lower contributions based on the model's assessment of feature importance, ultimately retaining the subset of features that most significantly improves model performance.
- Heuristic search [77]: Utilise heuristic strategies (e.g. genetic algorithms, simulated annealing, ant colony algorithms, etc.) to perform a global search in the feature space to find the optimal or near-optimal feature subset. This approach is effective for complex feature combinations and large search spaces.

2.3.3 Embedded-based Methods

Embedded-based methods integrate the feature selection process into the model training, leveraging the model's own parameter learning and optimization mechanisms to automatically identify and retain sensitive features for prediction results [78]. The following are common embedded-based methods.

- Regularization [79]: Introduce $\mathcal{L}_1$ or $\mathcal{L}_2$ regularization terms during model training to constrain feature coefficients, achieving automatically selecting and retaining the most influential sensitive features for prediction results.

- Tree models [80]: Evaluate information gain, gini impurity reduction or purity improvement during node splitting to quantify the contribution of each feature to model decisions (e.g. decision tree, random forest, gradient boosting decision tree, etc.) and identify highly important and sensitive features.

2.3.4 Reduction-based Methods

Reduction-based methods transform the original high dimensional feature space into a low dimensional representation through mathematical mapping, effectively compressing the number of features and eliminating redundancy while preserving as much critical information as possible [81]. The following are common reduction-based methods.

- Linear reduction [82]: Utilize linear techniques (e.g. rthogonal transformations or matrix decomposition, etc.) to project high-dimensional feature space onto low dimensional linear subspaces. This approach can effectively eliminate features linear correlations while retaining the global structure of the original feature (e.g. principal component analysis, linear discriminant analysis, non-negative matrix factorization, etc.).
- Non-linear reduction [83]: Employ non-linear transformation techniques (e.g. manifold learning, kernel methods, etc.) to embed features into a low dimensional non-linear space. This method can effectively capture the local neighborhood relationships and manifold structures in the original feature space (e.g. kernel principal component analysis, t-distributed stochastic neighbor embedding, isometric mapping etc.).

2.4 Intelligent Intensity Recognition

Intelligent intensity recognition establishes a mapping between selected features and cavitation intensity through a recognition model based on TML. To achieve this goal, the recognition model needs to be trained and learned on labeled cavitation samples. According to current research progress, we briefly introduce five commonly used TML methods for CIR in the following sections.

2.4.1 SVM-based Approaches

Support vector machine (SVM) is a supervised learning method based on statistical learning theory, which is widely used in classification, regression and anomaly detection tasks [6]. Its fundamental idea is to find an optimal hyperplane in the feature space to maximize the interclass margin, achieving effective separation of samples. Given a training dataset $\{\mathcal{X}, \mathcal{Y}\} = (x_i, y_i)$ with N samples, $x_i \in \mathbb{R}^d$ represents the feature vector of the i-th sample and $y_i \in \{+1, -1\}$ denotes its corresponding class label, the basic optimization objective of SVM can be expressed as:

$$\begin{array}{c} \min\limits_{w,b} \frac{1}{2}\|w\|^2 \\ \text{s.t.} \;\; y_i(w^{\mathrm{T}}x_i + b) \geq 1, \;\; i = 1, 2, \ldots, N \end{array}, \tag{1}$$

where w is the normal vector of the hyperplane and b is the bias term. In practical applications, due to noise interference and overlapping class boundaries, it is difficult for samples to satisfy the strict linear separability assumption. Therefore, SVM introduces slack variable ξ_i to construct a soft-margin classifier, as shown in Figure 3. The optimization objective is adjusted as follows:

$$\begin{array}{c} \min\limits_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum\limits_{i=1}^{N}\xi_i \\ \text{s.t.} \;\; y_i(w^{\mathrm{T}}x_i + b) \geq 1 - \xi_i, \;\; \xi_i \geq 0 \end{array}, \tag{2}$$

where C is the penalty factor used to control the balance between margin maximization and classification error minimization. In addition, SVM also introduces kernel methods to implicitly map the original features to a high-dimensional feature space. The typical kernel functions include radial basis kernel, polynomial kernel and sigmoid kernel, which are crucial role in accurately modeling complex patterns.

The application of SVM to CIR are systematically summarized in Table 2. According to the research results, the SVM have exhibited excellent performance in CIR for equipment such as pumps, turbine and pipes. For the above diagnostic objects, the SVM-based methods need to able to recognize multiple flow cavitation states, not only limited to the binary classification of cavitation and non-cavitation. Therefore, one-versus-rest (OVR) and one-versus-one (OVO) strategies have become solutions for SVM [84]. In addition, the researchers improved the diagnostic accuracy of modifying the SVM and optimizing the SVM parameters. For the former, researchers applied the modified SVM to CIR, such as least square SVM [85], proximal SVM [58], wavelet SVM [85] and one-class SVM [86], which all achieved better diagnostic performance than the traditional SVM. For algorithm optimization, researchers focused on simplifying the complex solution process and optimizing parameter selection of SVM, such as particle swarm optimization-based SVM [62], cuckoo search algorithm-based SVM [87] and butterfly optimization algorithm-based SVM [57].

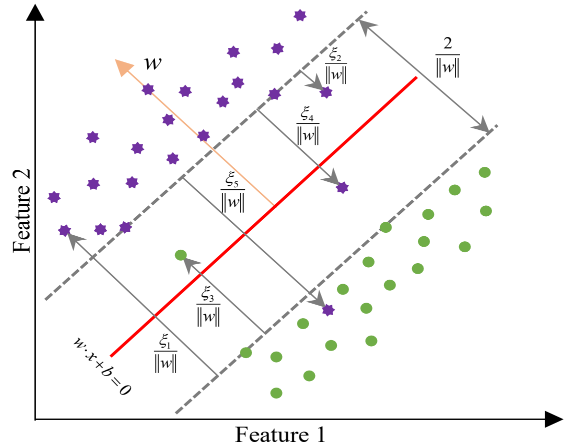

Figure 3: Schematic diagram of a SVM. The red solid line and the gray dashed line represent the separating hyperplane and the margin boundaries, respectively.

Table 2: Summary of applications of SVM-based methods in cavitation intensity recognition.

Objects	References	Signals
Pump	[34], [57], [58], [59], [62], [84], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101], [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115]	Vibration, Pressure, Current, Acoustic
Turbine	[94], [116], [117], [118], [119]	Vibration, Acoustic
Pipe	[85], [87], [120], [121], [122], [123]	Ultrasonic, Pressure, Acoustic
Propeller	[86], [124]	Vibration

2.4.2 DT-based Approaches

Decision tree (DT) is a supervised learning method for classification and regression tasks, which makes decisions at each internal node by partitioning the feature space into distinct subregions based on feature values [7]. The decision at each node is made by evaluating a specific feature and splitting the data into subsets according to a threshold value. Given a training dataset $\{\mathcal{X}, \mathcal{Y}\} = (x_i, y_i)$ with N samples, $x_i \in \mathbb{R}^d$ represents the feature vector of the i-th sample and y_i denotes its corresponding class label, the objective of DT is to recursively split the data at each node in order to create a tree structure that minimizes a measure of impurity, as shown in Figure 4. The basic optimization objective of DT is as follows:

$$\begin{gathered}\min_{S} \sum_{i=1}^{N} I(y_i|S) \\ \text{s.t.} \begin{cases} G(S) = 1 - \sum_{c=1}^{C} p(c|S) \\ E(S) = -\sum_{c=1}^{C} p(c|S) logp(c|S) \end{cases},\end{gathered} \tag{3}$$

where $I(y_i|S)$ is a measure of impurity, e.g. Gini impurity $G(S)$ or entropy $E(S)$, S represents the current subset of the data at given node and $p(c|S)$ is the proportion of class c sample in subset S. To prevent overfitting, the DT are often pruned by setting a maximum depth or by requiring a minimum number of samples in each leaf node. In addition, the DT can be enhanced by ensemble methods, such as random forests (RF) [125], gradient boosting machines (GBM) [126], extreme gradient boosting (XGBoost) [127], light gradient boosting machine (LightGBM) [128] and extremely randomized trees (ERT) [129], which combine multiple DTs to improve performance and reduce overfitting.

The application of DT and its derived methods to CIR are comprehensively summarized in Table 3. Based on the research results, the DT and its its derivatives have also been widely applied in CIR for equipment such as pumps, turbines, pipelines and valves. For the above diagnostic objects, DT-based methods are able to deal with both binary classification of cavitation and non-cavitation and multi-class recognition of different cavitation states. In addition, researchers have proposed a variety of improved DT methods, such as RF [91, 130] and XGBoost [48], which effectively

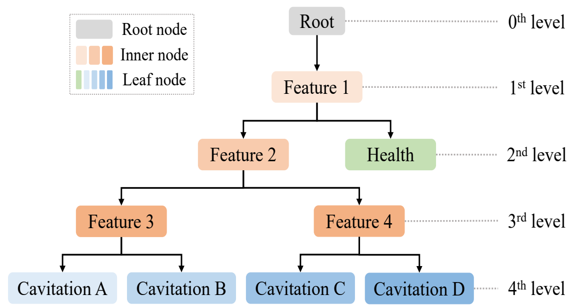

Figure 4: Schematic diagram of a DT. In general, the root node represents the entire sample set.

overcome the shortcomings of traditional DTs by ensemble learning and gradient boosting mechanisms. Furthermore, Kamali et al. [131] employed a combination of bayesian optimization with DT to automatically select hyperparameters.

Compared to SVM-based approaches, DT-based methods have natural interpretability and can automatically generate explicit diagnostic rules without relying on additional expert interpretation. In addition, DT-based methods are able to perform effective diagnosis even in the presence of missing data, which exhibits strong robustness. However, DT-based methods are often prone to suffer from overfitting, leading to weak generalization and compromising their effectiveness in complex diagnostic tasks. It is also worth noting that the design of many DT-based models still depends on expert knowledge, which restricts their universality and flexibility in certain application scenarios.

Table 3: Summary of applications of DT-based methods in cavitation intensity recognition.

Objects	References	Signals
Pump	[35], [84], [91], [130], [131], [132], [133], [134], [135], [136], [137], [138], [139], [140], [141]	Vibration, Current, Acoustic, Ultrasonic, Pressure
Turbine	[117], [142], [143], [144], [145], [146], [147]	Acoustic, Vibration, Pressure, Ultrasonic
Pipe	[48], [121], [148], [149]	Acoustic, Vibration
Valve	[48], [150], [151]	Acoustic, Vibration

2.4.3 ANN-based Approaches

Artificial neural network (ANN) is a traditional supervised learning method based on multilayer perceptrons (MLP), which is commonly applied to classification and regression tasks [8]. Its basic structure consists of an input layer, several hidden layers and an output layer, which achieves feature mapping through forward propagation and parameter updating using back propagation, as shown in Figure 5. Given a training dataset $\{\mathcal{X}, \mathcal{Y}\} = (x_i, y_i)$ with N samples, $x_i \in \mathbb{R}^d$ represents the feature vector of the i-th sample and $y_i \in \mathbb{R}^l$ denotes its corresponding class label. During the forward propagation process, the input data x_i are sequentially transmitted through each layer. Each layer receives the output of the previous layer as input, first calculates the weighted sum of that input, then performs a nonlinear transformation and passes the result to the next layer. The specific process is as follows:

$$(x_i^h)_j = \sigma(\sum_{i=1}^{n_{h-1}} w_j^h \cdot x_i^{h-1} + b_j^h), \tag{4}$$

where $(x_i^h)_j$ is the output of the j-th neuron in the h-th hidden layer, w_j^h is the weight between the neurons in the previous layer, b_j^h is the bias of the j-th neuron in the h-th hidden layer, σ represents the activation function (e.g. Sigmoid, ReLU, Tanh, etc.). The predicted output of ANN is:

$$(\hat{y}_i)_k = \sigma^{out}(\sum_{i=1}^{n_H} w_j^{out} \cdot x_i^H + b_j^{out}), \tag{5}$$

where $(\hat{y}_i)_k$ is the predicted output of the k-th neuron in the output layer, σ^{out} represents the activation function (Sigmoid and Softmax), w_j^{out} and b_j^{out} are the weights and bias of the output layer, respectively. The optimization objective of ANN minimizes the error between the predicted output and the groundtruth:

$$\min_\theta \sum_{i=1}^{N} \mathcal{L}(y_i, \hat{y}_i), \tag{6}$$

To achieve the above objective, the training parameters w and b are updated by gradient descent during the back propagation, as detailed below:

$$w^* \leftarrow w - \eta \cdot \frac{\partial \mathcal{L}}{\partial w}, \qquad b^* \leftarrow b - \eta \cdot \frac{\partial \mathcal{L}}{\partial b}, \tag{7}$$

where η is the learning rate, $\partial\mathcal{L}/\partial w$ and $\partial\mathcal{L}/\partial b$ are the gradients with respect to parameter w and b, respectively. In general, ANN consists of MLP, radial basis function neural network (RBFNN) [152], self-organizing map (SOM) [153] and hopfield neural network (HNN) [154], adaptive resonance theory network (ARTN) and so on [155].

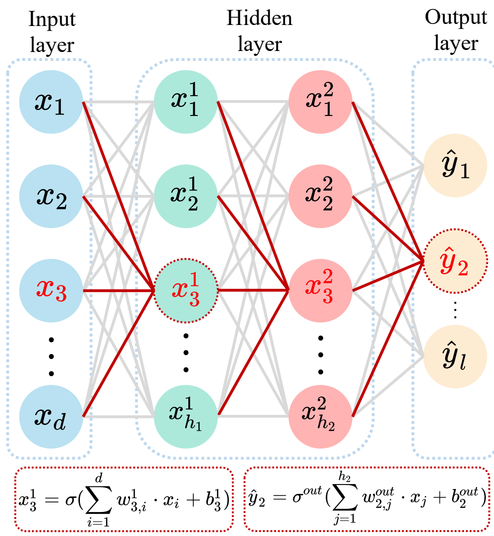

Figure 5: Schematic diagram of a ANN with two hidden layers.

The application of ANN to CIR are systematically reviewed in Table 4. As shown in Table 4, ANN-based methods have been widely applied to CIR in various hydraulic machinery and fluid systems, such as pumps, turbines, pipes and propeller. In particular, pump-related research focused on the variety of signal types, which reflects their comprehensive employment of multi-source information in cavitation monitoring. For pipelines and valves, acoustic, pressure and vibration measurements are commonly used for effective detection of local cavitation. In general, ANN-based methods is widely used on different objects and multiple signal sources, which demonstrates the universality and adaptability of ANN to CIR task.

Table 4: Summary of applications of ANN-based methods in cavitation intensity recognition.

Objects	References	Signals
Pump	[47], [60], [61], [91], [94], [111], [112], [113], [114], [115], [117], [156], [157], [158], [159], [160], [161], [162], [163], [164], [165], [166], [167], [168], [169], [170], [171], [172], [173], [174], [175], [176], [177], [178]	Current, Pressure, Vibration, Acoustic, High-speed images
Turbine	[94], [179], [180], [181], [182], [183], [184], [185]	Vibration, Pressure, Ultrasonic, High-speed images
Pipe	[85], [186], [187], [188]	Acoustic, Pressure
Valve	[189], [190]	Acoustic, Vibration
Propeller	[191]	Vibration

Compared to SVM and DT-based methods, ANN-based CIR methods can effectively capture potential features in multi-source monitoring signals to achieve high performance of different equipment cavitation states. However, ANN-based method still faces two challenges in engineering applications. First, the parameter size and complexity of the model dramatically increase with the dimension of the input data, which reduces the training efficiency and result in overfitting. Second, the ANN-based models show a typical black-box nature without theoretical foundation, making its diagnostic results difficult to support operation and maintenance decisions.

2.4.4 Other Approaches

In addition, other methods are also widely employed in FIR, such as k-nearest neighbours (KNN), expert system (ES). We will briefly introduce them in this subsection.

KNN-based Approaches. K-nearest neighbours (KNN) is a distance-based supervised learning method, which is typically used for classification and regression tasks [9]. The core idea is that given a predicted sample, the distance is firstly calculated between this sample and all labelled samples in the taring set. Then, the k nearest neighbours are found. Finally, the output of the sample is predicted based on the class or value of these k neighbours, as shown in Figure 6.

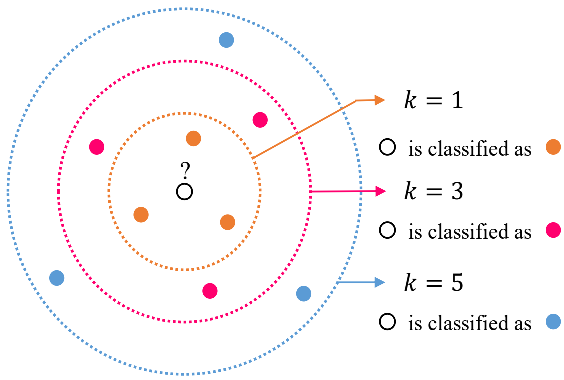

Figure 6: Illustration of a KNN algorithm.

KNN has received much attention in intelligent CIR research, especially in pumps [84, 89, 192], turbines [117] and valves [150]. Han et al. [84] proposed a KNN-based method for detection cavitation in centrifugal pumps using vibration and current signals. Paolo et al. [91] attempted a KNN-based model based on vibration signal for a hydraulic axial piston pump. Sousa et al. [117] developed a method for identifying incipient cavitation in wind turbines by extracting statical features of vibration signals and applying a KNN-based model. In addition, some researchers investigated the modified KNN models to enhance cavitation intensity diagnostic effects. Kermani et al. [193] presented a fuzzy KNN-based method for recognizing the cavitation intensity of dam spillway utilising pressure signals. Zeng et al . [194] proposed a method integrating dual-tree complex wavelet transform with variational mode decomposition and Bayesian optimized locally weighted KNN algorithm for intelligent recoignition of multi-state cavitation in vortex pumps based on current signals.

Although KNN has simplicity and effectiveness, it has several limitations in practical applications. First, the model is very sensitive to the choice of distance metric and parameter k, and inappropriate settings can significantly affect the final performance. Second, it has high computational complexity during the inference stage since it needs to calculate the distance between the test sample and all the training samples, resulting in extremely low efficiency in large-scale datasets. Third, it is very sensitive to irrelevant or redundant features. Finally, the basic KNN connot automatically perform feature weighting or learn the importance of features, causing it to depend on feature preprocessing to obtain the desired performance.

ES-based Approaches. Expert system (ES) is a rule-based artificial intelligence models that emulate the decision making process of human experts by encoding domain knowledge into a knowledge base and inference engine, which is widely used in condition monitoring of fluid machinery [10]. The core of ES is to utilise predefined logic rules extracted from practical experience and expert knowledge to parse the sensor signals and identify different cavitation states, as shown in Figure 7. Sakthivel et al. [41] proposed a combination of rough set rule extraction and a fuzzy inference system to achieve cavitation detection and intensity diagnosis in centrifugal pump using vibration signals. Saeid et al. [195] presented a vibration signal diagnosis method based on the combination of FFT feature extraction and adaptive fuzzy inference system for intelligent fault diagnosis of centrifugal pumps. Azadeh et al. [196] developed a fuzzy rule-based inference system approach to realise timely diagnosis of cavitation states in centrifugal pumps.

Although ES has a strong interpretability, it faces several limitations in practical applications. First, the construction of ES is heavily relies on a priori knowledge of domain experts, resulting in time-consuming and labor-intensive process of knowledge acquisition. Second, ES cannot update knowledge base or optimize inference rules online, making it difficult to adapt to new fault patterns. Third, ES typically relys on deterministic logical reference, resulting in weakly

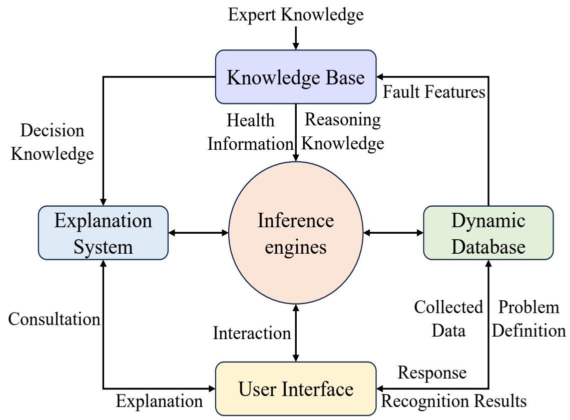

Figure 7: Schematic diagram of an ES.

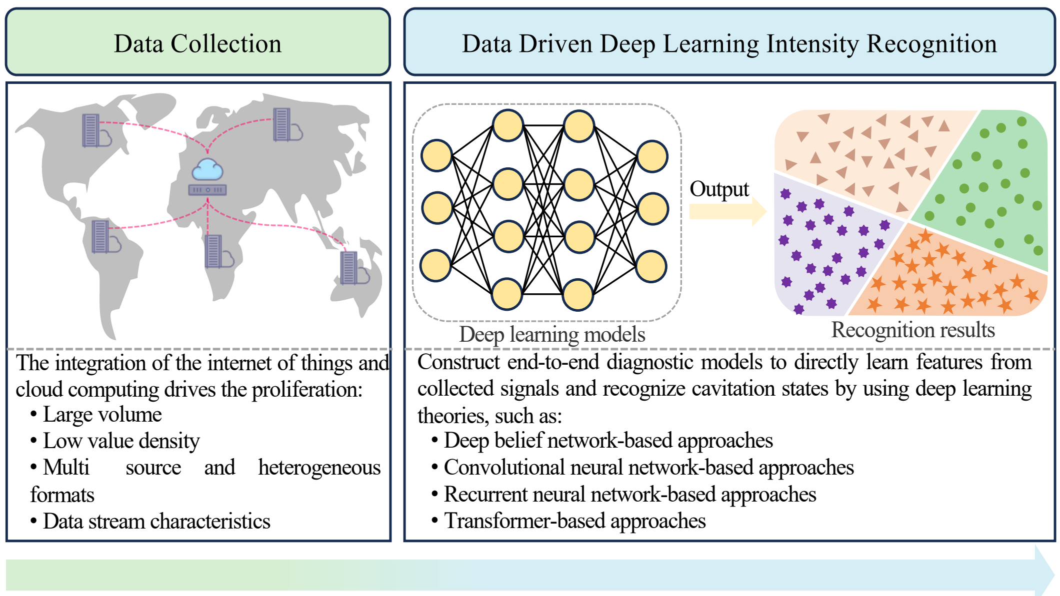

Figure 8: Diagnosis procedure of cavitation intensity recognition using deep learning methods, which consists of data acquisition and data-driven deep learning intensity recognition.

handling noise and incomplete information in signals. Finally, ES adds new fault types or modifies new rules to require redesigning the rule base, resulting in system inflexibility.

3 Data Driven Deep Learning

In contrast to TML approaches, data-driven deep learning (DL) methods have gained attention in CIR since their powerful end-to-end feature learning and representation capabilities. Instead of relying on manually extracted features, DL models can automatically extract multi-level features directly from original sensor signals, which can reduce the dependence on expert experience and complex signal preprocessing [197]. A typical DL-based CIR pipeline normally consists of data collection and end-to-end intensity recognition, as shown in Figure 8, which will be detailed in the following subsections.

3.1 Data Collection

In modern industrial monitoring systems, data collection is the basis for CIR and other equipment health diagnostics. The process typically relies on a variety of sensors and control system to continuously acquire signals from the equipment under a wide range of operating conditions. The collected data not only presents the classical characteristics of volume, velocity, variety and veracity, but also exhibits domain-specific attributes determined by industrial environment [198].

- Large volume: Over long-term operation, monitoring systems for equipment continuously record multiple channel signals. High-frequency measurement (e.g. vibration signals from gearboxes, acoustic emission signals from cavitation-prone pipelines segments) can significantly increase the data volume.
- Low value density: Although a large amount of sensor data is collected, only a small portion is directly related to cavitation events or fault states. The vast majority of the records correspond to the normal operating cditions of the equipments and some of data may be of poor quality due to transmission interruptions, environmental disturbances or sensor failures.
- Multi-source and heterogeneous formats: Multiple sensors (e.g. vibration, pressure, acoustic, etc.) are often integrated in industrial monitoring, resulting in heterogeneous data in both structure and sampling rate.
- Data stream characteristics: The development of technologies (e.g. internet of things, high-speed networks, GPU computing, edge computing, etc.) make it possible to acquire real-time, high-frequency monitoring data streams, enabling immediate access to machine health information.

Cavitation-related monitoring data are collected from the target system across different operating conditions. The acquisition devices include acoustic emission sensors, energy sensors, pressure sensors, vibration accelerometers, ultrasonic sensors and high-speed camera (more detailed see Table 1), which are placed at key locations to capture the entire "occurrence-development-collapse" process of cavitation. All signals are recorded simultaneously by the industrial data acquisition unit and stored in original waveforms and lightly preprocessed forms, ensuring the data covers a wide range of cavitation intensities, which satisfies the training requirements of DL models.

3.2 End-to-end intensity recognition

The DL model directly performs feature learning and cavitation intensity prediction simultaneously from raw monitoring data, eliminating manual feature extraction and feature selection. In general, its architecture includes an automatic feature learning module and a prediction module. The DL model training is based on end-to-end error backpropagation, while optimizing the parameters of both the feature and prediction layers to highly match the learned representation with the recognized target. According to current research progress, we briefly introduce four typical DL structures for CIR in the following sections.

3.2.1 DBN-based Approaches

Deep belief network (DBN) is a class of generative graphical models stacked with multiple layers of restricted boltzmann machine (RBM) [11]. It is able to learn hierarchical abstract features of the input data in an unsupervised learning manner and achieve classification or regression by supervised fine-tuning, as shown in Figure 9. The RBM is an undirected bipartite graph consisting of a visible layer v and a hidden layer h, which are fully connected between the layers and unconnected within the same layer. Its energy function is:

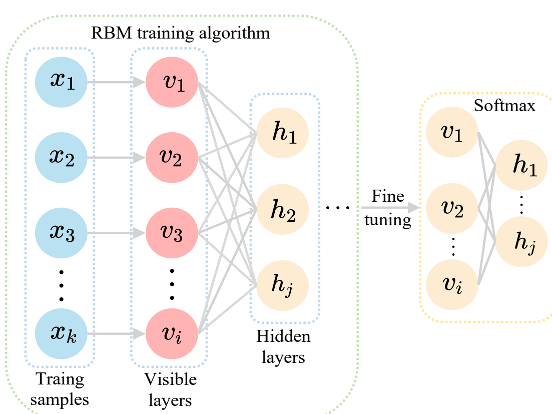

Figure 9: Schematic diagram of a DBN.

$$E(v,h) = -\sum_{i=1}^{m} a_i v_i - \sum_{j=1}^{n} b_i h_j - \sum_{i=1}^{m}\sum_{j=1}^{n} v_i w_{ij} h_j, \tag{8}$$

where w_{ij} is the weight matrix, a and b are the bias terms of the visible and hidden layers, respectively. Based on the Equation 8, the marginal distribution of the visible units can be calculated as:

$$P(v,h) = \frac{1}{Z} e^{-E(v,h)}, \tag{9}$$

where $Z = \sum_{v,h} e^{-E(v,h)}$ represents partition function. The activation conditions for visible and hidden units are defined as follows:

$$\begin{cases} P(v_i = 1|h) = \sigma(\sum_{j=1}^{m} w_{ij} h_j + a_i) \\ P(h_j = 1|v) = \sigma(\sum_{i=1}^{n} w_{ij} v_i + b_j) \end{cases}, \tag{10}$$

where σ denotes the Sigmoid function. Based on contrastive divergence (CD), the weight matrix w_{ij} is updated as follows:

$$\Delta w_{ij} = \eta(< v_i h_j >_{data} - < v_i h_j >_{recon}), \tag{11}$$

where, η is the learning rete, $< v_i h_j >_{data}$ and $< v_i h_j >_{recon}$ represent the expected values of the product $v_i h_j$ under the data distribution and reconstructed distributions, respectively.

DBN has been widely applied in CIR due to its strong capability in learning hierarchical and discriminative features from raw, high-dimensional and noisy monitoring signals. Wang et al. [199] proposed a fast and effective cavitation diagnosis approach for hydraulic system vibration signals based on a DBN with sliding window spectrum feature. Huang et al. [200] presented an automatic weak cavitation recognition method for hydraulic systems based on the combination of multi-scale entropy feature extraction of fault-sensitive intrinsic mode function and DBN. Liu et al. [201] developed a method to improve the cavitation diagnosis performance of gear vibration signals by optimizing the number of hidden layer neurons and learning rate of DBN. Yan et al. [202] devised an improved data preprocessing method combined with a genetic algorithm optimized DBN to enhance cavitation diagnosis performance for actual gas turbine.

Although DBN exhibits strong capability in automatic feature learning, it also encounters several limitations in practical applications. First, the performance of DBN is highly dependent on the setting of hyperparameters, which typically require repeated tuning for different datasets. Second, DBN training involves layer-wise pretraining and fine-tuning, leading to relatively high computational cost and long training time.

3.2.2 CNN-based Approaches

Convolutional neural network (CNN) is a type of deep feedforward neural network inspired by the receptive field mechanism of the visual cortex, which is widely applied in computer vision [203, 204, 205, 206], speech recognition [207, 208, 209], natural language processing [210, 211, 212, 213], time-frequency signal analysis [214, 215, 216, 217] and so on [218, 219, 220, 221, 222]. Its basic structure typically consists of an input layer, several convolutional layers, pooling layers, fully connected layers and an output layer. The CNN achieves hierarchical automatic feature extraction through convolution and pooling operations, as shown in Figure 10, followed by nonlinear transformations via activation functions and finally performs classification or regression through fully connected layers. Given a training dataset $\{\mathcal{X}, \mathcal{Y}\} = (x_i, y_i)$ with N samples, $x_i \in \mathbb{R}^d$ represents i-th sample and $y_i \in \{+1, -1\}$ is the corresponding label. For a one dimensional convolutional network, the operation for the k-th feature map in the h-th layer can be expressed as:

$$x_{ik}^{h} = \sigma(\sum_{j} x_j^{h-1} \cdot w_{jk}^{h} + b_k^{h}), \tag{12}$$

where x_{ik}^{h} represents the output of the k-th feature map in the h-th layer, x_j^{h-1} is the j-th input feature map from the $(h-1)$-th layer, $\sigma(\cdot)$ is the activation function (e.g. ReLU, Sigmoid, Tanh, etc.), w_{jk}^{h} and b_k^{h} are the convolution kernel and bias corresponding to input channel j and output channel k, respectively. Pooling layers are used to reduce the spatial or temporal resolution of the feature maps and enhance invariance to translation and noise. For example, the max pooling can be formulated as:

$$p_k^{(h)}(u) = \max_{s \in \Omega_u} (x_{ik}^{h})(s), \tag{13}$$

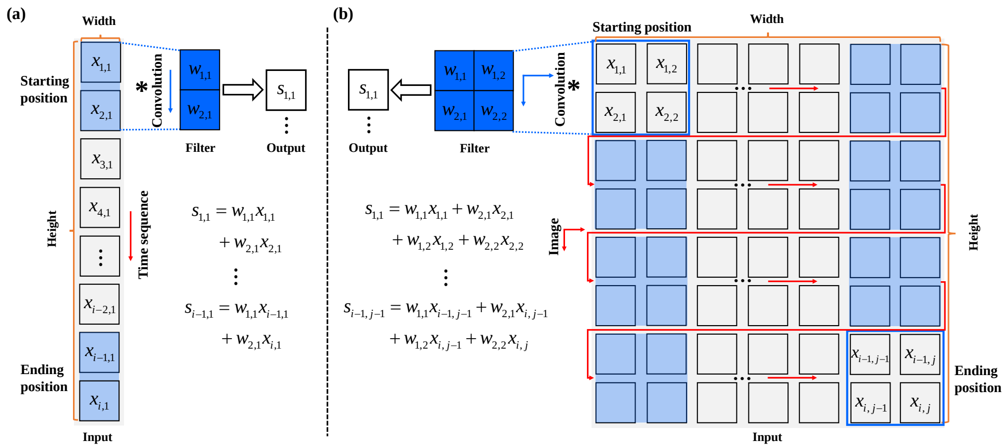

Figure 10: Schematic diagram of convolution operation. (a) and (b) show the working principle of 1D and 2D convolution, respectively.

where Ω_u denotes the pooling region centered at position u. After several convolution and pooling layers, the high level features are flattened and passed into fully connected layers. The predicted output of the k-th neuron in the output layer is computed as:

$$\hat{y}_{ik} = \sigma^{out}(\sum_j w_{jk}^{out} \cdot z_j + b_k^{out}), \tag{14}$$

where z_j denotes the j-th neuron output in the fully connected layer, $\sigma^{out}(\cdot)$ is typically Sigmoid or Softmax function, w_{jk}^{out} and b_k^{out} are the weights and biases of the output layer, respectively. The objective of CNN is to minimize the between the predicted output and the ground truth:

$$\min_\theta \sum_{i=1}^{N} \mathcal{L}(y_i, \hat{y}_i), \tag{15}$$

where θ represents the model parameters and are optimized using stochastic gradient descent (SGD) or its variants (Adam, RMSprop, etc.), with the update formulas:

$$w^* \leftarrow w - \eta \cdot \frac{\partial \mathcal{L}}{\partial w}, \qquad b^* \leftarrow b - \eta \cdot \frac{\partial \mathcal{L}}{\partial b}, \tag{16}$$

where η is the learning rate, $\partial \mathcal{L}/\partial w$ and $\partial \mathcal{L}/\partial b$ are the gradients with respect to w and b, respectively. In general, CNN can be classified into 1D CNN, 2D CNN and 3D CNN. Based on the above, researchers have developed various architectures, such as LeNet [12], AlexNet [223], VGGNet [224], DenseNet [14], ResNet [13], MobileNet [15], ShuffleNet [16].

The application of CNN to CIR are systematically reviewed in Table 5. As shown in Table 5, CNN-based methods have been widely applied to CIR in various hydraulic machinery and fluid systems, such as pumps, turbines, pipes, valve and propellers. Among these, pumps are the most extensively studied, with both 1D CNN and 2D CNN architectures being applied. Specifically, 1D CNN is mainly used for processing time series signals (e.g. acoustic, vibration, prsssure, current, etc.), while 2D CNN often relies on time-frequency representations or high-speed images to capture spatial features of cavitation. Research on turbines, pipes, propellers and valves is relatively limited, which indicates potential for further expansion. Many CNN-based studies directly employ established network architectures, which makes it challenging to fully tailor the models to the unique characteristics of CIR. In general, CNN-based CIR studies show a trend toward integrating multiple signal types and network structures, though the maturity varies across different objects.

Compared with DBNs, CNNs offer advantages in CIR, including automatic extraction of local features, reduced reliance on manual feature design and higher computational efficiency. In addition, CNNs also demonstrate higher performance and robustness when processing images and time-frequency two-dimensional features. However, CNNs have limited capability in capturing strong nonlinear and long-term dependency features and their performance is sensitive to the quantity and quality of training data.

Table 5: Summary of applications of CNN-based methods in cavitation intensity recognition.

Objects	Types	References	Signals
pump	1D CNN	[167], [225], [226], [227], [228], [229], [230], [231], [232], [233], [234], [235], [236], [237], [238], [239], [240], [241], [242], [243], [244]	Acoustic, Vibration, Pressure, Current, High-speed images
	2D CNN	[245], [246], [247], [248], [249], [250], [251], [252], [253], [254], [255], [256], [257], [258], [259], [260], [261], [262], [263], [264], [265], [266], [267], [268], [269], [270], [271], [272], [273], [274]	
Turbine	1D CNN	[239], [243], [275], [276], [277], [278], [279], [280], [281], [282]	Acoustic, Vibration, Pressure, Current
	2D CNN	[52], [283], [284], [285], [286], [287], [288]	
Pipe	1D CNN	[188], [289], [290], [291], [292], [293]	Acoustic
	2D CNN	[294], [295], [296]	
Propeller	1D CNN	[54], [297], [298]	Acoustic, Current, High-speed images
	2D CNN	[299], [300], [301], [302], [303], [304], [305], [306], [307]	
Valve	1D CNN	[289], [290], [291]	Acoustic, Vibration
	2D CNN	[295], [308]	

3.2.3 RNN-based Approaches

Recurrent neural network (RNN) is class of neural network models designed to capture temporal dependencies and sequential correlations in data [17]. Unlike CNNs, RNN introduce recurrent connections in hidden layer, allowing information from previous time steps to influence the current output, as shown in Figure 11. The basic operation of a vanilla RNN for a sequence $\{x_1, x_2, \cdots, x_T\}$ can be expressed as:

$$h_t = \sigma(W_{xh}x_t + W_{hh}h_{t-1} + b_h), \tag{17}$$

$$y_t = \sigma^{out}(W_{hy}h_t + b_y), \tag{18}$$

where h_t is the hidden state at time t, W_{xh}, W_{hh}, W_{hy} are the input-to-hidden, hidden-to-hidden and hidden-to-output weight matrices, respectively. b_h and b_y are biases, $\sigma(\cdot)$ is typically a nonlinear activation function and $\sigma^{out}(\cdot)$ is the output activation function. The objective function is to minimize the sequence prediction loss over all time steps:

$$\min_{\theta} \sum_{i=1}^{N}\sum_{t=1}^{T} \mathcal{L}(y_t^{(i)}, \hat{y}_t^{(i)}), \tag{19}$$

where $\theta = \{W_{xh}, W_{hh}, W_{hy}, b_h, b_y\}$ and are updated through backpropagation through time. To address the vanishing and exploding gradient issues in vanilla RNN, researchers have developed various architectures, such as LSTM [18], BiLSTM [309] and GRU [19].

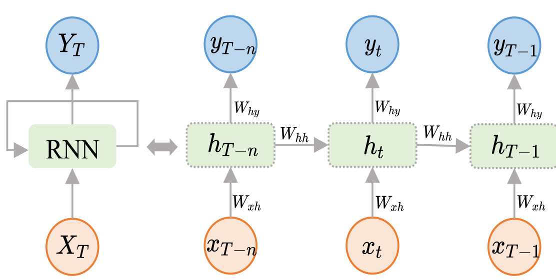

Figure 11: Schematic diagram of a RNN.

RNN-based approaches have been effectively applied to CIR. For instance, some research [150, 174, 310] directly applied LSTM to CIR of valves and pumps, respectively. Lee et al. [261] and Zhu et al. [311] proposed combining

CNN and RNN methods to achieve CIR in pumps using high-speed images and vibration time-frequency images, respectively. Zhang et al. [312] developed a multi-dimensional feature fusion method based on a convolutional gated recurrent unit to achieve CIR in centrifugal pumps. Liu et al. [313] designed a GRU-based method using vibration data to a realize CIR of firefighting pumps. Zhao et al. [314] presented a VMD-dung bettle optimization-GRU-attention model using pressure data to achieve CIR in pumps and turbines.

Compared to DBNs and CNNs, RNN-based models have superior capabilities in modeling temporal dependencies and capturing highly time-correlated signal patterns. However, their training process is often time-consuming and they are more susceptible to gradient vanishing and exploding issues. Moreover, their performance can degrade when data are insufficient or noisy.

3.2.4 Transformer-based Approaches

Transformer is a deep learning architecture entirely based on the attention mechanism, which has become the infrastructure for large language models [20, 315]. Unlike CNNs and RNNS, the Transformer discards recurrent and convolutional structures, instead of employing a fully parallelizable multi-head self-attention mechanism to model global dependencies, significantly improving training speed and long sequence modeling capability [316, 317]. A standard Transformer consists of an encoder and a decoder stack. The encoder comprises multi-head self-attention layers, positional encoding, feed forward network, residual connections and layer normalization, see Figure 12. The decoder adds masked self-attention and encoder-decoder attention mechanisms to the encoder. Given an input sequence $\mathcal{X} = [x_1, x_{2,} \cdots, x_N]$, linear projections are applied to obtain the Query, Key and Value matrices:

$$Q = XW_Q, \quad K = XW_K, \quad V = XW_V, \tag{20}$$

where W_Q, W_K, W_V are learnable weight matrices. The self-attention computation is defined as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V, \tag{21}$$

where d_k is the dimension of the key vectors. The multi-head self-attention mechanism computes h parallel attention heads and concatenates results:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\mathrm{h}_1, \dots, \mathrm{h}_h)W_O, \tag{22}$$

$$\mathrm{h}_i = \text{Attention}(QW_Q^i, KW_K^i, VW_V^i), \tag{23}$$

where W_O is the output projection matrix. Based on the above theories, researchers present a variety of improved architectures for different tasks, such as ViT [318], SwinT [319], BERT [320], Linformer [321] and CLIP [322].

Transformer as an emerging deep learning architecture that has also has been introduced into the field of CIR. For example, He et al. [285] proposed a model that combines Short-time Fourier Transform, generative adversarial network and Swin-Transformer to achieve CIR using vibration signal spectrograms. Jiang et al. [323] presented a combination of continuous wavelet transform and Swin Transformer method for CIR in centrifugal pumps. Shang et al. [324] developed a lightweight vision transformer model combining adaptive convolution and mobile vision transformer blocks to achieve early-stage CIR under complex and noisy conditions. Zhang et al. [325] designed a deep learning approach using mel-spectrogram representations combined with self-attention mechanisms to realise CIR from hydrofoil acoustic signals. Yu et al. [295] proposed a hierarchical knowledge-guided acoustic CIR method based on graph convolutional networks and reweighted hierarchical knowledge correlation matrices using various Transformer architectures.

Compared to CNNs, the application of Transformer is constrained by multiple factors, including the requirement for large-scale and high-quality labeled datasets, higher computational cost due to complex self-attention operations and the challenge of effectively modeling domain-specific features when applied to relatively small or noisy datasets. Transformer offers strong capabilities in capturing long-term dependencies and global contextual information, making it well suited for tasks with strong spatial and temporal correlations of signals. In addition, it has high flexibility in addressing multi-modal data. However, Transformer typically requires more computational resources and careful parameter tuning, which can make it less efficient for on-site or real-time monitoring scenarios. Furthermore, it is prone to overfitting and may struggle to generalize well compared to more lightweight structures in the case of insufficient training data.

4 Data-Knowledge Driven Deep Learning

In contrast to data-driven deep learning approaches, data-knowledge driven deep learning (DKDL) methods have attracted growing attention in CIR because they integrate physical knowledge with the strong feature learning capability

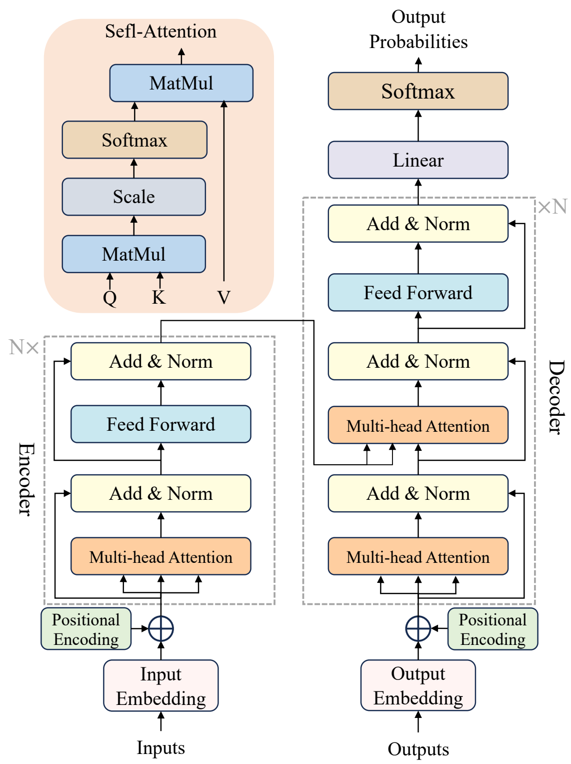

Figure 12: Schematic diagram of a Transformer.

of deep models. By embedding domain-specific physics, governing equations or expert heuristics into the learning process, DKDL not only can enhance model interpretability, but also ensure the predictions comply with fundamental physical principle. This hybrid paradigm effectively bridges the gap between data-driven inference and physics-based modeling. A typical DKDL pipeline for CIR generally includes data and knowledge collection, deep feature learning and physical knowledge learning, as shown in Figure 13, which will be detailed in the following subsections.

4.1 Data and Knowledge Collection

For DKDL framework, the data component utilises various signals acquired from different sensors described previously, which characterize the operating states of hydraulic machinery under various work conditions. On this basis, the model incorporates multiple types of physical knowledge from the hydraulic machinery domain, which are structured and formalized to support feature learning and recognition tasks [326]. These knowledge types include:

- Physical equations knowledge [327]: Includes fluid mechanics governing equations (e.g. Navier-Stokes equations), bubble dynamics equations (e.g. Rayleigh-Plesset equation) and cavitation inception criteria (e.g. cavitation coefficient), which describe the fundamental principle of liquid flow and cavitation formation.
- Domain expert knowledge [328]: Derived from the long-term practical experience and diagnostic heuristics of engineers (e.g. abnormal vibration patterns, acoustic characteristics, pressure variation rules, historical cases, fault mechanism analysis, determination rules, etc.), provides diagnostic basis and domain background information.
- Physical parameters knowledge [329]: Key physical quantities obtained during the operation or experimental monitoring of hydraulic machinery (e.g. flow rate, rotational speed, pressure values, temperature, etc.). These parameters reflect the operational state and cavitation occurrence conditions of the equipment, providing highly relevant physical information for models.
- Physical structure knowledge [31]: Covers the hierarchical and dependency relationships among target classes, the mutual exclusion or inclusion constraints between classes, the coupling and constraint relationships among physical variables and the structural layout and functional dependencies among hydraulic machinery components. This type of knowledge enables the model to incorporate multi-level correlation information during the learning process.

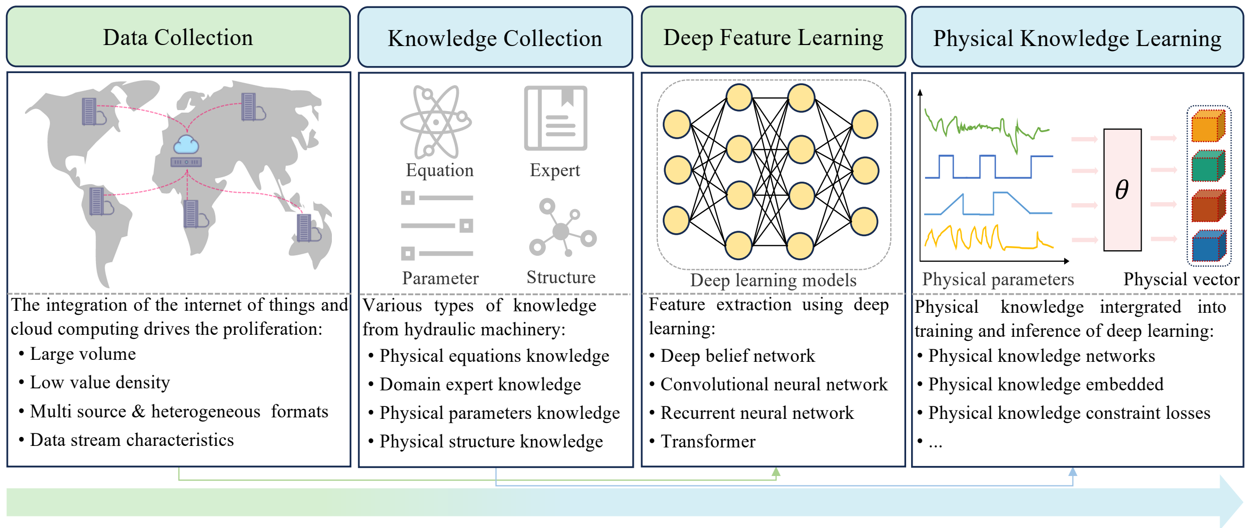

Figure 13: Diagnosis procedure of cavitation intensity recognition using data and knowledge driven deep learning methods, which consists of data acquisition, knowledge collection, deep feature learning and physical knowledge learning.

These knowledge can be used to construct physical constraints, enhance feature representations or directly construct physical knowledge networks, which effectively guides the model to learn discriminative patterns matching practical operating conditions and physical principle. The DKDL framework not only retains the automatic feature learning advantages of data-driven methods, but also significantly improves the physical consistency and generalization capability of recognition results.

4.2 Deep Feature Learning

Deep feature learning aims to utilize deep neural networks to automatically extract high-level feature representations from raw multi-source sensor data, supporting subsequent fusion with physical knowledge. The input data typically includes acoustic signals, vibration signals, pressure pulsation signals, current signals and cavitation flow field images captured by high-speed imaging, which are preprocessed and directly fed into the deep learning model to perform end-to-end feature extraction. The deep learning architectures employed are consistent with data-driven deep learning approaches.

4.3 Physical Knowledge Learning

Physical knowledge learning aims to seamlessly integrate fundamental physical principle, domain experience, key physical parameters and structural relationships information into both the training and inference processes of deep models, which can enhance the physical consistency, cross-condition generalization capability and interpretability of CIR results. In view of current research progress, three representative physical knowledge learning approaches are briefly introduced in the following sections.

4.3.1 Physical Knowledge Network

The physical knowledge network (PKN) is an essential component of the DKDL framework. Its core principle involves explicitly incorporating the physical principle and characteristics of hydraulic machinery through customized network architectures, enhancing the physical consistency and interpretability of CIR. Unlike generic data-driven deep learning architectures, the PKNs incorporate specific physical mechanisms into their hierarchical design, connection patterns and kernel construction, enabling a better capture of intrinsic relationships among multidimensional physical variables, equipment structures and signal features, as shown in Figure 14. In current research, typical PKN architectures include:

- Hierarchical neural networks [291, 330]: Design network architectures based on hierarchical relationships among cavitation intensity labels or physical variables, enhancing the ability to discriminate multi-level cavitation states.

- GCN-based hybrid networks [295, 331]: Leverage graph convolutional netwotk (GCN) to model the correlation relationships between physical variables or cavitation intensity labels and integrate them with other feature learning networks (e.g. CNNs, RNNs, Transformer, etc.), enabling effective guidance and constraint of deep features.
- Transformation-domain neural works [332, 333]: Directly replace or modify certain components of traditional data-driven neural networks (e.g. activation functions, kernel function, inter-layer weights, etc.) with signal transformation methods (e.g. wavelet transform, Fourier transform, etc.), enabling the model to acquire time-frequency domain or frequency domain feature extraction capabilities at the structural level.

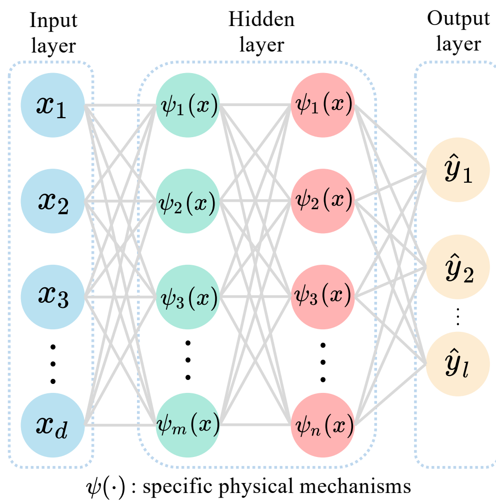

Figure 14: Schematic diagram of a PKN with two physical mechanism hidden layers.

Compared to data-driven deep learning approaches for CIR, the application of PKNs in this field remains in its infancy and the current research is relatively limited. For hierarchical neural networks, Gou et al. [291] proposed a two-stage sub-master transition hierarchical network for CIR using acoustic signals from valve and pipeline systems. Wen et al. [334] presented a hierarchical convolutional neural network method to achieve bearing fault diagnosis using vibration signals. Guo et al. [335] developed a hierarchical learning rate adaptive deep convolutional neural network to implement bearing fault diagnosis using vibration signals. For GCN-based hybrid networks, Sha et al. [295] proposed a hierarchical knowledge-guided acoustic CIR method based on graph convolutional networks and reweighted hierarchical knowledge correlation matrices. Li et al. [331] presented a graph isomorphic network with a spatio-temporal attention mechanism to achieve fault diagnosis of hydraulic axial piston pumps using weighted graph data constructed from univariate signals. Hua et al. [336] designed a graph convolutional transformer network method to perform fault diagnosis of slurry circulating equipment using frequency-domain graph data constructed from high-frequency vibration signals. For transformation-domain networks, Gao [337] presented a neural-wavelet network to achieve process diagnostics based on magnetic flowmeter data and power load demand prediction using electrical load signals. Won et al. [338] proposed a method combining wavelet coefficient variance features with neural networks to realise cavitation detection in pumps using pressure signals. Wang et al. [339] suggested a method combining wavelet transform, rough sets and a partially linearized neural network to achieve centrifugal pump system fault diagnosis. Rani et al. [340] introduced a probabilistic Fourier neural operator method to conduct process fault detection using multivariate historical process data. Tan [341] proposed a Fourier neural network and generalized single hidden layer network method to perform multi-fault diagnosis. Yu et al. [342] developed a fast Fourier convolutional gated current unit method to perform fault prediction using remaining useful life data.

Compared to data-driven deep learning approaches, the PHN exhibits higher physical consistency and interpretability in CIR and demonstrate better generalization under small-sample or noisy conditions. However, the design of PKNs relies heavily on domain expert knowledge and involves complex construction. In addition, the training process requires simultaneous optimization of data features and knowledge constraints, resulting in relatively high computational costs.

4.3.2 Physical Knowledge Embedded

The core concept of physical knowledge embedded (PKE) is to explicitly integrate domain-specific knowledge into data-driven deep learning models, enabling feature extraction and physical constraints to operate simultaneously. Unlike purely data-driven feature learning, this approach injects physical information directly into the structural design or feature stream of the model, which balances data representation capability with physical consistency and enhances generalization and interpretability in CIR [343], as shown in Figure 15. Given a dataset $\{\mathcal{X}, \mathcal{K}\} = \{(x_i, k_i)\}_{i=1}^N$ with x_i represents i-th sample and k_i represents the corresponding physical knowledge, the embedding process can be expressed as:

$$F_{\text{embed}} = \Phi(f_{\text{data}}(\mathcal{X}), f_{\text{know}}(\mathcal{K})), \tag{24}$$

where $f_{\text{data}}(\cdot)$ is the operator for data-driven feature extraction, $f_{\text{know}}(\cdot)$ is the mapping operator for physical knowledge and $\Phi(\cdot, \cdot)$ denotes the fusion strategy. The common forms of physical knowledge embedding include:

- Feature-level fusion [344]: At the model input layer, raw sensor data and physical parameters are concatenated or fused, and uniformly encoded into the network so that both data features and physical information are provided from the outset.
- Intermediate embedding [345]: Domain specific prior knowledge calculated from physical principle are introduced into intermediate layers as additional channels, allowing alongside data-driven features toward subsequent layers.
- Knowledge-guided attention [346]: Physical knowledge is generated as attention weights or masked areas to guide the model to focus on physically significant regions or variables during feature learning, enhancing discriminative and physical interpretability of features.

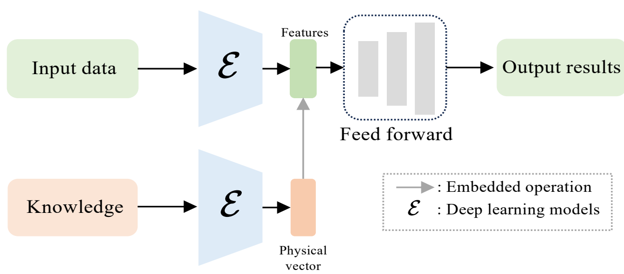

Figure 15: Schematic diagram of a PKE.

In contrast to data-driven deep learning approaches for CIR, the use of PKEs in this domain is still at an early developmental stage and the current research is relatively limited. For example, Sha et al. [295] developed target classes hierarchical knowledge embedding representation learning based on convolutional neural network and word embedding technique for CIR. Miglianti [347] proposed a method combining semi-empirical approaches and hybrid machine learning models to perform propeller cavitation noise prediction. Chen et al. [304] presented a hierarchical transformer method to achieve ship fault recognition using acoustic noise signals. Qiao et al. [348] designed a prior knowledge embedding contrastive attention learning network method to conduct rolling bearing fault diagnosis using vibration signals. Du et al. [349] suggested a knowledge-embedded deep belief network to achieve fault diagnosis of building chillers.

Compared to PHNs, PKEs directly embeds domain physical knowledge into the input layer or intermediate feature layers, offering flexible modification and low implementation cost, which allows for rapid application to existing deep neural networks. However, the physical knowledge embedded by PKE primarily consists of local parameters or prior features, making it difficult to construct complex global physical relationships. When the knowledge is incomplete or biased, it is susceptible to noise and variations in distribution. Therefore, PKE is more suitable for providing lightweight physical information enhancement to existing models, whereas PHN is better suited for tasks requiring in-depth characterization of multi-level physical mechanisms.

4.3.3 Physical Knowledge Constraint Loss

Physical knowledge constraint loss (PKCL) aims to explicitly incorporate physical principle, empirical rules or operational boundaries into the optimization objective of data-driven deep learning models [350], as shown in Figure 16. The PKCL can guide the neural network to produce outputs consistent with know physical mechanisms and domain constraints by penalizing predictions violating physical feasibility, improving the reliability and interpretability of the deep learning model [21]. Given a dataset $\{\mathcal{X}, \mathcal{Y}, \mathcal{K}\} = \{(x_i, y_i, k_i)\}_{i=1}^N$, where x_i denotes the i-th input sample, y_i is the ground truth label and k_i represents the corresponding physical knowledge. The total loss function can be expressed as:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{data}}(f_\theta(\mathcal{X}), \mathcal{Y}) + \lambda \mathcal{L}_{\text{phy}}(f_\theta(\mathcal{X}), \mathcal{K}), \tag{25}$$

where $\mathcal{L}_{data}$ is the primary task data loss, $\mathcal{L}_{phy}$ is the physical knowledge constraint loss to measure the degree of violation of physical principle or constraints, λ is a weighting factor controlling the balance between task performance and physical consistency, $f_\theta(\cdot)$ denotes the deep model represented by the parameter θ. The common forms of PKCL include:

- Boundary condition penalty: Restrict the output prediction values within predefined physical ranges.
- Physical principle penalty: Measure the deviation between predicted values and calculated values derived from physical equations or empirical models.
- Trend consistency penalty: Enforce the output of prediction results to remain consistent with the inherent properties of physical processes.

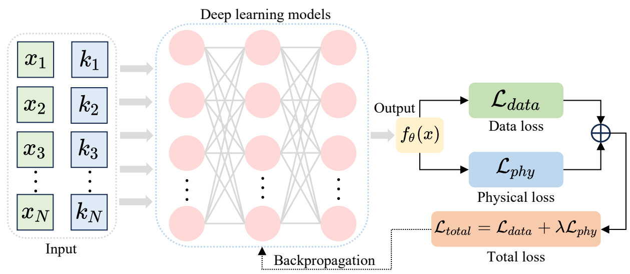

Figure 16: Schematic diagram of a PKCL.

The PKCL has attracted significant attention and been widely applied in solving ordinary differential equations and other physical-related modeling tasks, but its research in CIR is still in the early developmental stage. For instance, Wang et al. [351] proposed a physical informed neural network method to achieve fault severity identification in axial piston pumps using pressure signals. Keshun et al. [352] presented a dynamic physical with a data-driven quadratic neural network and bidirectional LSTM to conduct rolling bearing damage assessment using vibration signals. Keshun et al. [353] developed a sound-vibration physical-information fusion constraint-guided deep learning method to perform bearing fault diagnosis using acoustic and vibration signals. Pan et al. [354] designed a physics-guided neural network to deliver condenser fault diagnosis using key physical indicator signals. Li et al. [355] proposed a physical-guided multi-teacher knowledge distillation network method to achieve external gear pump fault diagnosis using multimodal signals.

Compared with PKE, the PKCL introduces physical constraints into the loss function, synchronizing the data-driven learning process with physical consistency optimization. Its advantages lie in the ability to continuously impose the supervision from physical principle on the model outputs during the training phase, which enhances the interpretability and physical credibility without modifying the network structure. However, PKCL is sensitive to the design of constraint terms and weight selection, which may lead to difficulties in model optimization when the physical knowledge is incomplete or noisy.

5 Discussions

With the continuous development of cavitation intensity recognition (CIR) technology, research has evolved from traditional machine learning reliant on manually extracted features to deep learning with end-to-end feature extraction, which develops physics-guided diagnostic models incorporating physical knowledge. At the end of this review, we attempt to describe a roadmap and discuss challenges of CIR based on a systematic analysis of relevant literature from 2004 to 2025, as shown in Figure 17, aiming to inspire readers to understand potential research trends and directions in this field over the next five to ten years.

5.1 High-Quality Multi-Source Data

High-quality multi-source data is the foundation for reliable cavitation intensity recognition (CIR) and related industrial equipment fault diagnosis. Current datasets generally suffer from insufficient sample size, imbalanced fault categories, disproportionate distribution between normal and fault conditions and incomplete operational condition coverage. These issues not only hinder comprehensive feature learning during the training phase, but also reduce diagnostic performance and stability in practical applications. In addition, multi-source data (e.g. acoustic signals, vibration signals, pressure

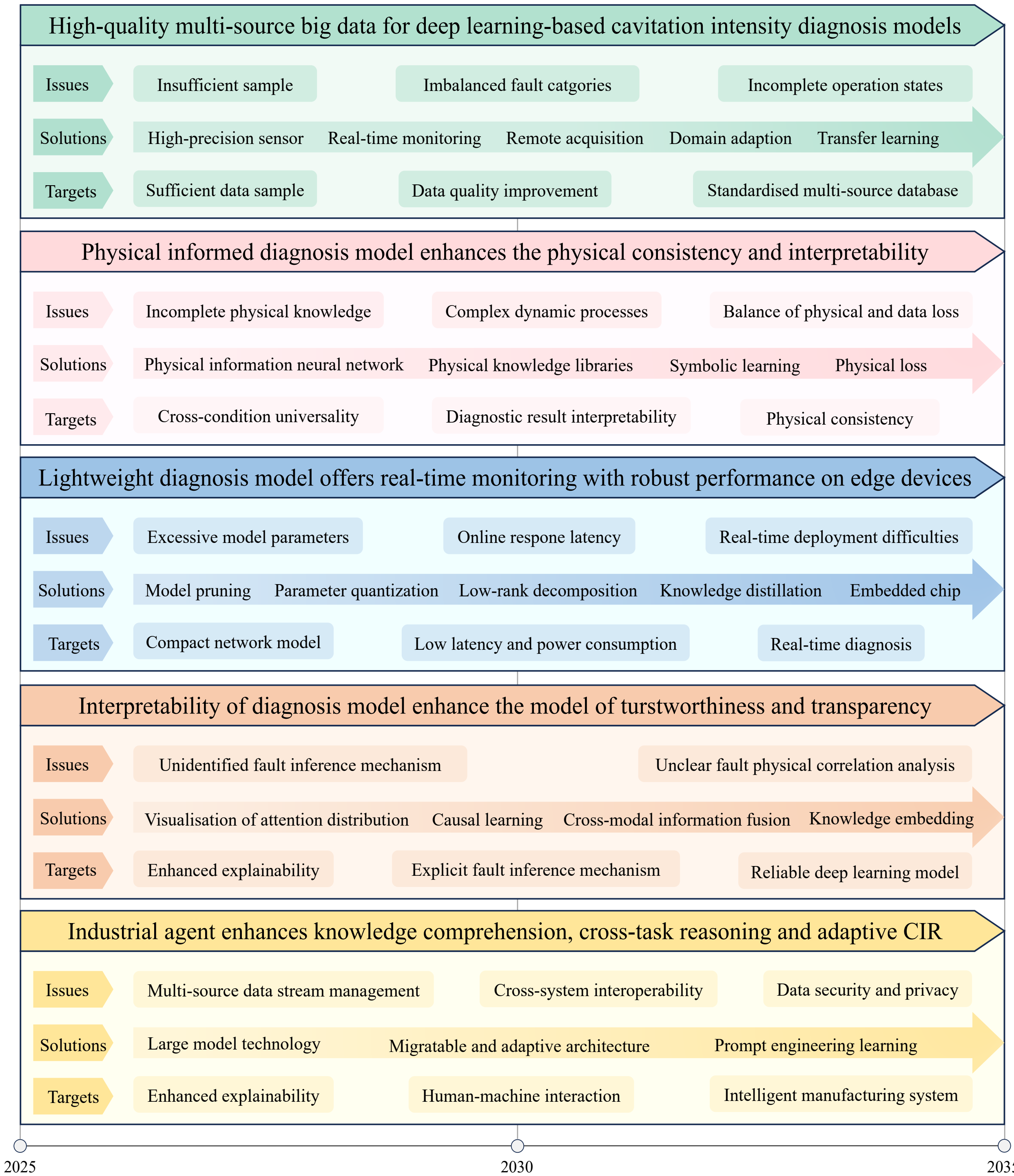

Figure 17: A roadmap outlining the application of machine learning to intelligent cavitation intensity recognition.

pulsations, current signals, high-speed imaging, etc.) are seldom acquired synchronously, which can lead to temporal misalignment and feature distortion during multimodal fusion.

In the future, the focus should be on establishing standardized multi-modal data collection protocols to ensure comparability and interoperability of data collected from different experimental platforms. At the same time, low-cost and high-accuracy sensing technologies should be explored to enhance the feasibility of data acquisition and large-scale cavitation status database should be established using real-time monitoring and remote acquisition technologies. Meanwhile, the integration of data augmentation techniques (e.g. signal simulation, noise modeling, signal mixing, etc.), domain adaptation and transfer learning can be employed to migrate knowledge from similar operating conditions or related equipment to expand the training sample space. In addition, hybrid modeling frameworks integrating simulated and experimental data can also effectively alleviate sample insufficiency and enhance the model robustness and cross-scenario adaptability.

5.2 Physics Informed Diagnostic Model

Physics informed diagnostic models can enhance the physical consistency and interpretability of fault diagnostic results by fusing data-driven learning with domain physical knowledge, which can strengthen the credibility of decision credibility and engineering applicability. Although physical information neural networks (PINNs), physical knowledge embedding (PKE) and physical knowledge constraint loss (PKCL) have achieved success in science and engineering fields (e.g. fluid mechanics, structural health monitoring, energy systems, etc.), they are still in infancy in cavitation intensity recognition. In addition, the existing studies mainly focus on embedding individual physical laws or simplified models and lacks a unified deep integration framework. In practice, this class of methods mainly face challenges including the difficulty of translating multi-scale coupled dynamic equations of the cavitation process into directly usable constraints, the the incompleteness or noise in physical knowledge of industrial systems and the difficulty of balancing physical constraints with the flexibility of data-driven models.

Future research should explore automated and adaptive knowledge integration by leveraging machine-readable physical formula libraries, symbolic learning and graph-based knowledge representations to enable the automatic extraction and dynamic embedding of physical knowledge. In addition, physics-oriented interpretable tools should be developed to allow engineers to intuitively understand the model's decision process.

5.3 Lightweight Diagnostic Model

In industrial embedded monitoring systems, computational efficiency and hardware resource limitations create an urgent demand for lightweight diagnostic models, while requiring the model complexity be reduced without significantly compromising performance. However, many current deep learning models contain millions or even hundreds of millions of parameters, which not only increases storage and computational burdens but also makes real-time deployment difficult and limits adaptability to low-power edge devices. Furthermore, in multi-source data scenarios, models usually need to simultaneously process multimodal signals, resulting in traditional large-scale models are more prone to overfitting or response delays for on-line applications.

Future research should focus on designing task-specific compact network architectures for multi-source inputs, incorporating multimodal feature fusion and knowledge guidance into the architecture. In terms of compression techniques, model pruning, parameter quantization, low-rank decomposition and knowledge distillation can be explored. In particular, multi-teacher distillation strategies for handing missing modalities, which can retain critical feature extraction capabilities while reducing computational costs. In addition, hardware optimization algorithms should be integrated, such as operator acceleration for embedded chips and FPGA or ASIC deployment schemes. At the same time, exploration of neuromorphic computing and event-driven neural networks is also warranted to further lower latency and power consumption. Furthermore, lightweight models must also incorporate stability design in noisy environments, ensuring they maintain high reliability and performance in real-world industrial conditions.

5.4 Interpretability of Diagnostic Model

In safety-critical domains (e.g. aerospace, marine, energy, etc.), interpretability is a core factor in establishing trust in intelligent diagnostic systems. However, current deep learning models lack explicit reasoning about fault mechanisms and physical correlation analysis, making it difficult for maintenance personnel to fully trust the diagnostic conclusions of models. Existing studies aimed at improving interpretability primarily include visualizing attention weight distributions to reveal regions of interest for the model, conducting sensitivity analysis on multimodal inputs to evaluate feature contributions and embedding physical knowledge to link decision processes with fault evolution mechanisms. Nevertheless, there are still significant technical challenges in enhancing interpretability while maintaining diagnostic performance under complex multi-source data and non-linear feature scenarios.

Future research should focus on constructing diagnostic model architectures with interpretability as a core design principle, taking interpretability requirements into account during the network structure design stage. Causality-driven feature learning methods should be introduced to model the relationships between input features and fault causal chains, enhancing the scientific rigor and credibility of inferences. In addition, visualization and explanation tools based on domain expert decision logic should be developed, enabling model outputs to be presented in an intuitive manner. Moreover, research into explainability should incorporate cross-modal information fusion strategies, enabling complementary insights from different types of sensor data. This approach enhances trustworthiness and transparency while preserving the model's high performance and robustness in real-world industrial applications.

5.5 Industrial Agents

Industrial agents as an autonomous fault monitoring and decision control unit, which exhibit significant potential for intelligent cavitation intensity recognition in complex manufacturing systems. These agents integrated with industrial internet of things platforms, which can manage real-time multi-source data streams, perform distributed diagnostics and coordinate maintenance task. With the maturation of large model technology, its vertical applications have endowed industrial agents with enhanced knowledge comprehension and cross-task reasoning capabilities, enabling more precise feature extraction, complex pattern recognition and natural human-machine interaction in CIR. The industrial agent ensures interoperability across heterogeneous systems, safeguarding data exchange security and privacy during industrial data exchange. Furthermore, the transferable agent architecture adapts to diverse operational conditions. Future research should explore integrating large model prompt engineering with reinforcement learning, adaptive diagnostic strategies and cloud-edge-end collaborative frameworks, which can significantly enhance fault diagnosis performance interpretability and real-time performance in industrial operations.

6 Conclusions

In this paper, we systematically review of the development of cavitation intensity recognition (CIR), focusing on the evolution from traditional machine learning methods to physical-informed deep learning frameworks. In general, the development of CIR can be divided into three stages. In the past, CIR was implemented through step of data collection, manual feature extraction and intensity recognition. In this stage, traditional machine learning models were able to accomplish the recognition tasks, which are heavily depended on expert domain knowledge. With the rapid progression deep learning in recent years, end-to-end deep learning models have been extensively applied to automatically learn features from multi-modal cavitation data, significantly enhancing recognition performance and robustness. However, data-driven learning models cannot guarantee physical consistency, rendering them unsuitable for practical engineering applications. To address this limitation, physical-informed diagnostic models integrate domain knowledge into the deep learning process, enhancing the model interpretability and generalization capabilities under complex operating conditions. Finally, we discuss the challenges of CIR including multi-source data standardization, model lightweighting, interpretability and engineering deployment. In addition, we outline a roadmap for future studies. This review aims to systematically summarize the development of CIR technologies, providing valuable references for intelligent cavitation diagnosis in industrial applications.

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