SMTNet: Hierarchical Cavitation Intensity Recognition Based on Sub-Main Transfer Network

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Abstract

With the rapid development of smart manufacturing, data-driven machinery health management has been of growing attention. As one of the most popular methods in cavitation intensity recognition, deep learning (DL) has been achieving remarkable results. However, current DL methods are restricted by the assumption that all target classes should be treated equally and exclusively. In situations where some classes are more difficult to be distinguished compared to others and where classes might be organised in a hierarchy of categories, current DL methods can not work well. In this study, a novel hierarchical cavitation intensity recognition framework using Sub-Main Transfer Network, termed SMTNet, is proposed to classify acoustic signals of valve cavitation. SMTNet model outputs multiple predictions ordered from coarse to fine along a network corresponding to a hierarchy of target cavitation states. Firstly, a data augmentation method based on Sliding Window with Fast Fourier Transform (Swin-FFT) is developed to solve few-shot problem. Secondly, a 1-D double hierarchical residual block (1-D DHRB) is presented to capture sensitive features of the frequency domain valve acoustic signals. Thirdly, hierarchical multi-label tree is proposed to assist the embedding of the semantic structure of target cavitation states into SMTNet. Fourthly, experience filtering mechanism is proposed to fully learn a prior knowledge of cavitation detection model. Finally, SMTNet has been evaluated on two cavitation datasets without noise (Dataset 1 and Dataset 2), and one cavitation dataset with real noise (Dataset 3) provided by SAMSON AG (Frankfurt). The prediction accuracies of SMTNet for cavitation intensity recognition are as high as 95.32%, 97.16% and 100%, respectively. At the same time, the testing accuracies of SMTNet for cavitation detection are as high as 97.02%, 97.64% and 100%. In addition, SMTNet has also been tested for different frequencies of samples and has achieved excellent results of the highest frequency of samples of mobile phones.

Keywords Valves acoustics signal; Cavitation detection; Sub-main transfer neural network; 1-D double hierarchical residual block; Hierarchical multi-label tree; Hierarchical cavitation intensity recognition

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1 Introduction

Cavitation is defined as the phenomenon that bubbles form on the solid surface when the pressure at the contact point of the liquid and the solid surface is lower than its vapor pressure \[1, 2, 3\]. When the bubble flows to the place where the liquid pressure exceeds the bubble pressure, the bubble collapses and the collapse instantaneously produces a great impact and high temperature \[4, 5\]. Furthermore, severe pitting and corrosion is formed on the solid surface \[6\].

Cavitation can bring many potential dangers, especially for valves, pumps or pipes. These potential dangers can quickly cause damage to valves, pumps and pipes \[7\]. On the one hand, cavitation can cause corrosion and damage to valves, pumps and pipes \[8\], and the internal structure of vibration and noise are increased \[9\] due to the collapse and rupture of bubbles \[10\]. On the other hand, the flow rate and fluid bulk modules inside the valve, pumps and pipes are reduced due to cavitation \[11, 12\]. Therefore, valves, pipes, pumps and related components are at the largest risk. Most industries are damaged by cavitation, such as SAMSON AG and the manufacturing plants of valves, pipes and pumps \[13\]. In the worst case, cavitation can lead to the closure of the factory. Therefore, it is necessary to detect the cavitation of valves, pumps and pipes at its early stages so as to ensure security and reliability of the test rack system with control valve.

The cavitation is usually detected by comparing the fault and healthy conditions under the monitored signals. According to the type of data, it can be divided into cavitation detection based on vibration signal and acoustic signal. Recently, some researchers have extracted features from vibration or acoustic signals, and then used machine learning to detect cavitation.

Sakthivel et al. \[14\] extracted 11 statistical features from the vibration time domain signal. Then, these features are input into the C4.5 decision tree \[15\] to classify the bearing fault, seal fault, impeller fault, bearing and impeller fault together and cavitation. Muralidharan et al. \[16\] used the Continuous Wavelet Transform (CWT) \[17\] to replace the statistical feature extraction from vibration signals. Then the features after the CWT are input into a decision tree algorithm to classify cavitation, impeller fault, bearing fault and both bearing and impeller fault. In addition, Muralidharan et al. \[18\] also studied the influence of different families and different levels of CWT for fault diagnosis of single-piece centrifugal oils using SVM. Samanta et al. \[19\] extracted features from the original and pre-processed signals as the input of two different classifiers of the support vector machine (SVM) and the artificial neural network (ANN) to identify normal and defective bearings. The parameters of SVM and ANN are optimized by genetic algorithms \[20\]. And results explained the importance of feature selection to the classifier. Yang et al. \[21\] extracted 4 statistical features from the vibration time domain signals as the input of SVM to detect cavitation and no cavitation of the butterfly valve. Bordoloi et al. \[22\] proposed an SVM method using vibration signal data of bearing block and pump casing to diagnose blockage level and cavitation intensity. Panda et al. \[23\] extracted statistical features from the time domain vibration signal of the pump as the input of SVM to predict cavitation and flow block. Rapur et al. \[24\] proposed an intelligent detection method based on SVM to classify mechanical fault and flow rate using motor line current and pump vibration signal. Shervani-abar. \[25\] proposed a multi-class cavitation detection method based on the vibration signal of the axial flow pump using SVM.

Zouari et al. \[26\] studied a vibration signal fault detection method for centrifugal pumps using neural network and neuro-fuzzy technology. Rajakarunakaran et al. \[27\] proposed a centrifugal pump fault detection using a feedforward network and a binary adaptive resonance network (ART1). Siano et al. \[28\] proposed a method combining ANN and nonlinear regression to diagnose cavitation of time domain vibration signals. Nasiri et al. \[29\] extracted features from the vibration signal of the centrifugal pump as the input of the neural network to detect cavitation. Tiwari et al. \[30\] extracted 6 statistical features from the time domain pressure data, and then these features are input to the neural work to detect blockage and cavitation. Potocnik et al. \[31\] extracted spectral and psychoacoustic features from the valve acoustic data and then these features are input to a variety of machine learning algorithms to classify the cavitation, flow noise, whistling and rattling. Zhao et al. \[32\] proposed a deep learning method to extract features from non-stationary vibration signals and diagnose centrifugal pump faults. Jia et al. \[33\] studied a deep neural network (DNN) to directly extract features from the original rolling element bearings and planetary gears data set for fault diagnosis. Pasha et al. \[34\] applied the use of raw acoustic time-frequency spectrograms as input to an RNN for condition monitoring of a sintering plant. Chao et al. \[35\] investigated a 1-D CNN with multi-channel of vibration signals as input for cavitation intensity recognition of high-speed axial piston pumps. Wen et al. \[36\] proposed a transfer learning based convolutional neural network (TCNN) for fault diagnosis. In addition, 1-D CNN have been widely applied for time series data, including electrocardiogram detection \[37\], electroencephalogram diagnosis \[38\] and bearing fault diagnosis \[39, 40, 41\] and so on.

It can be found from the literature review that recent researches on cavitation or fault detection are developed using traditional machine learning (ML, like, decision tree, SVM, or ANN) or deep learning (DL, like, DNN or CNN). In traditional ML-based classification researches, the labeled signals collected are initially pre-processed. Then, result-oriented manual features (HF) are extracted to generate a master feature vector (MFV). Finally, the MFV is fed as input...
to a traditional ML algorithm to build a cavitation or fault detection model. However, the main limitation of traditional ML-based methods is the extraction of result-oriented features. The DL method revolutionises the traditional ML approach by eliminating the HF engineering step. The main advantage of DL is that it is end-to-end learning combined with HF engineering and does not require specific domain knowledge. While DL largely transfers the burden from the human expert to the machine, it also lacks the characteristics of the human expert for the process of cavitation and fault detection. At the same time, it has a low accuracy for detecting the fine state of cavitation ("cavitation choked flow", "constant cavitation", "incipient cavitation" and "non cavitation") according to our previous researches.

In order to address the limitations of the above researches, motivated by the characteristics of the process of diagnosing cavitation by professional engineers, this study proposed an accurate and computationally feasible two-step hierarchical cavitation intensity recognition framework using sub-main transfer network (SMTNet) to classify acoustic signals of valves into four distinct classes ("cavitation choked flow", "constant cavitation", "incipient cavitation" and "non cavitation"). SMTNet is a hierarchical-based multi-class model constructed by two neural networks (i.e. sub neural network and main neural network) arranged in parallel on two levels. And both the sub and main networks consist of a series of 1-D hierarchical residual blocks (1-D DHRBs). In the first level, the sub classifier is placed to classify the valve acoustic signal into two distinct classes [cavitation, non-cavitation]. In the second level, the main classifier is responsible for predicting the three fine classes [cavitation choked flow, constant cavitation, incipient cavitation] of valve acoustic signals that have been detected as the cavitation state. Extensive experiments are conducted on the SMTNet and supervised machine learning and deep learning algorithms to achieve high-performance classification of four different levels of cavitation states in valve acoustic signals. The main contributions to this work are summarized below.

- A novel deep learning-based hierarchical classification model for cavitation intensity recognition is proposed.
- In order to tackle the few-shot learning problem, the Sliding Window with Fast Fourier Transform (Swin-FFT) data augmentation method is introduced in the study.
- The 1-D Double Hierarchical Residual Block (1-D DHRB) with large kernel is proposed as a feature extractor to capture sensitive features of valve acoustic signals.
- Hierarchical multi-label tree is proposed to assist the embedding of the semantic structure of target cavitation states into deep learning models.
- The mechanism of experience filtering is proposed to fully learn a priori knowledge of the cavitation detection model.
- The proposed method is tested on three datasets of valve acoustic signals provided by SAMSON AG in Frankfurt and compared with the state-of-the-art methods.
- The impact of the proposed SMTNet for cavitation detection and cavitation intensity recognition is investigated for different frequencies of samples of acoustic signals.

The remainder of this paper is organized as follows. Section 2 introduces the acquisition of valve cavitation detection data. Section 3 presents a deep learning based hierarchical cavitation intensity recognition method. Section 4 introduces the case research. Section 5 discusses the results of overall cavitation intensity recognition and the impact of different frequencies of samples for the proposed method. The conclusion and future researches are drawn in Section 6.

2 Experimental setup and data acquisition

SAMSON AG devised a test rack with control valve (SAMSON AG type 3241, DN 80, PN40, Kvs 25 with positioner type 3730-6) running water as the flowing medium inside to generate different flow status by gauging operation conditions accordingly: upstream pressure, downstream pressure and the valve stroke. The test bench is equipped with a set of sensors to measure the temperature of the test medium $T$, the pressures upstream $p_1$ and downstream $p_2$ of the test valve and the volumetric flow rate $Q$. Additionally, the test valve mounted inside the bench measures the absolute valve stroke $h$ and the sound intensity $I_p$ with a special sensor directly mounted on the valve body. Furthermore, the test bench includes two additional control valves upstream and downstream of the test valve. A control system controls the pumps as well as these two valves to modify the total volumetric flow through the test bench. The two additional valves are used to influence the upstream and downstream pressure around the test valve. All sensors and the test valve are mounted between these two external control valves. The pipes between the external valves and the test valve are long enough to ensure an undisturbed flow for proper measurements. Water, which can also be heated, was used as the test medium for all tests. The water temperature was maintained at $25 \text{ - } 40^\circ \text{C}$ in order to hold the vapor pressure nearly constant and to eliminate the influence of temperature on the cavitation.
Figure 1: Schematic view of the test rack at SAMSON AG (Figure provided by SAMSON AG).

(a) Cavitation Choked Flow  
(b) Constant Cavitation  
(c) Incipient Cavitation  
(d) Non cavitation

Figure 2: Acoustic signals in (a)-(d) for cavitation choked flow, constant cavitation, incipient cavitation and non-cavitation, respectively.
Two piezo elements were introduced to record directly the structure-borne noise of the valve: one placed on the body of the control valve and the other one to the NAMUR at the bonnet. Furthermore two microphones were placed in a distance of 1m to the control valve to record the airborne noise in a frequency range between 40 Hz up to 20 kHz: one high-end microphone as well as a low cost microphone which typically is used in smartphones. Figure 1 shows a schematic view of the experimental setup, where the data is generated.

By varying the differential pressure at various constant upstream pressures of the control valve different operation conditions were adjusted, five flow status are induced in the acoustic signal data: cavitation choked flow, constant cavitation, incipient cavitation, turbulent flow and background no-flow. The status turbulent flow is a flow through the control valve without any cavitation noise. Starting at a certain differential pressure ratio within a certain range only a few vapor bubbles will be generated and the implosion of these bubbles is causing an increase of the noise emission, which is defined as incipient cavitation. By increasing the concentration of vapor bubbles also the noise emission is increasing up to a noise maximum which is defined as constant cavitation. Achieving the noise maximum also the concentration of the vapor bubbles is maximum which leads to a choked flow condition with cavitation and a decreasing noise behavior.

Figure 2 shows an exemplary comparison of time waveform of the acoustic signals for cavitation choked flow, constant cavitation incipient and non cavitation. In this study, an intelligent SMTNet method is used to directly extract the sensitive features from acoustic signals and to recognize the levels of cavitation intensity.

3 Methods

3.1 Motivation

How do professional engineers perform cavitation intensity recognition? A recent report states that professional engineer diagnosis is hierarchically structured, where the initial diagnosis is fairly broad and then into fewer refined diagnostic states [42, 43]. In the field of artificial intelligence, there is a similar concept known as hierarchical classification methods.

Figure 3 shows the concept of our hierarchical cavitation intensity recognition. When a acoustic signal of valves is detected, it is firstly determined whether it is cavitation or not. If it is recognized as cavitation, it would be further identified as to which level of cavitation it belongs. If it is recognized as non-cavitation, the recognition is completed. This hierarchical cavitation intensity recognition framework can improve the accuracy of cavitation intensity recognition and reduce the recognition time. In addition, the hierarchical cavitation intensity recognition framework is more similar to the process of diagnosing cavitation in humans.

3.2 Hierarchical cavitation intensity recognition

Motivated by the motivation, a novel two-step hierarchical cavitation intensity recognition framework using sub-main transfer network (SMTNet) has been proposed (see Figure 4). In the first step, a cavitation detection model for cavitation and non cavitation is built. In the second step, the model for cavitation intensity recognition (‘cavitation choked flow’,...
When performing classification, the outputs of the sub and the main neural networks of SMTNet each have as many predictions as the levels of the corresponding hierarchical multi-label tree (introduced in 3.5), respectively. In particular, considering the hierarchical multi-label tree as shown in Figure 4, the signal for acoustic contains the hierarchical multi-label of [cavitation, non cavitation]. The signal of cavitation contains the hierarchical multi-label of [cavitation choked flow, constant cavitation, incipient cavitation]. When the acoustic signal is fed into the SMTNet, the sub neural network will output two corresponding predictions as the data stream passes, and the main neural network will output three corresponding predictions as the data stream passes.

The SMTNet is composed of a sub neural network and a main neural network, where the sub neural network is used for cavitation detection and the main neural is applied for cavitation intensity recognition. Figure 4(b) and Figure 4(c) show the structure of the sub neural network and the main neural network, respectively. They are very similar in structure and both consist of a series of 1-D DHRB (see Figure 4(d)). The 1-D DHRB consists of several convolutional layers of different size (Conv), batch normalization layers (BN), rectified linear unit (ReLU) activation function and two shortcuts (introduced in 3.4).

During the training stage, we apply hierarchical classification to separate the training steps of the cavitation detection model and the cavitation intensity recognition model. After the step of cavitation detection, the cavitation intensity recognition model is constructed using hierarchical transfer learning from the cavitation detection model. During the testing stage, the experience filtering (described in 5.6) is proposed to reuse the results of the model of cavitation detection to improve the accuracy of the cavitation intensity recognition model.

The knowledge gained from classifying cavitation and non cavitation are reused to improve the accuracy of the cavitation intensity recognition model. During the testing stage, the experience filtering is used to improve the accuracy of the cavitation intensity recognition model. The signal of cavitation contains the hierarchical multi-label of [cavitation choked flow, constant cavitation, incipient cavitation]. The signal of cavitation choked flow contains the hierarchical multi-label of [cavitation choked flow, constant cavitation, incipient cavitation]. When the acoustic signal is fed into the SMTNet, the sub neural network will output two corresponding predictions as the data stream passes, and the main neural network will output three corresponding predictions as the data stream passes.
3.3 Data augmentation

In general, machine learning is driven by big data\cite{44}. However, our Dataset 1, Dataset 2 and Dataset 3 only have 356, 806 and 160 acoustic signal data, respectively. Therefore, data augmentation is very essential. Data augmentation can improve the accuracy of the model and prevent over-fitting. And it can teach the model the desired invariance and robustness properties \cite{45, 46}.

Considering purposely steady flow status (i.e. it’s always the same fluid status class within the individual measurement duration with 3-second or 25-second time-length) in each recorded sample and fine resolution for the sensor. One can actually split each sample into several pieces which still can hold enough essential information for detection. However, with independent characteristics per piece due to the intrinsic randomness of the noise emission, given the piece is not so short. Therefore, according to the above theory, a data augmentation method based on sliding window with fast fourier transform (Swin-FFT) is proposed, see Figure 5. This method involves two main steps:

\textbf{Figure 5: Data augmentation based on sliding window with fast fourier transform.}

\begin{itemize}
  \item Step 1: The signal data is split by a sliding window.
  \item Step 2: The time-domain data is transformed into frequency-domain data by Fast Fourier Transform (FFT).
\end{itemize}

The Swin-FFT contains only one parameter, which is the size of window \( W_{\text{size}} \). And \( W_{\text{size}} \) will be analyzed and determined by experiments, which can reduce the effect of experts’ bias on cavitation intensity recognition and cavitation detection (see section \( \S4 \)) as much as possible.

3.4 1-D double hierarchical residual block

Residual block (RB) is an important module of the residual networks (ResNet). RB is based on the idea of connecting blocks of convolutional layers by using skip connection. The output of the RB is \( H(x) = F(x) + x \). RB changes the network learning objective from \( H(x) \) to \( H(x) - x \). This structure can help optimize the trainable parameters in error backpropagation to avoid the problem of vanishing and exploding gradients. And it can assist in building deeper network structures.

Motivated by this, we have developed an one dimensional convolution-based double hierarchical residual block (1-D DHRB) to improve valve cavitation detection and cavitation intensity recognition. Both RB and 1-D DHRB have two Conv and BN layers. However, the size of two Conv layers of 1-D DHRB are different and hierarchical compared to the traditional RB. The filter size of the first Conv layer is \( 32 \times 32 \), and the second Conv layer has a filter size of \( 16 \times 16 \) (The filter size has been determined through several experiments). 1-D DHRB uses large convolution kernels compared to RB, which can capture sensitive features of the acoustic signal with fewer layers of the network. And the size of the first Conv layer is twice the size of the second Conv layer, which helps the network to focus more on the sensitive features of the feature map of the first Conv layer.

The 1-D DHRB adds a shortcut compared to the traditional RB. One shortcut for 1-D DHRB is the identity \( x \), the other shortcut for 1-D DHRB is a non-linear function \( F(x) \) of identity \( x \) through one Conv and BN layer. The output of 1-D DHRB is given in Equation (1).

\[ H(x) = F(x) + F(x) + x \] (1)
3.5 Hierarchical multi-label tree

In the hierarchical multi-label tree (see Figure 4), the fine multi-labels are the target classes and the task of hierarchical classification is the predicted classes at each level (i.e. tree). They are presented as leaves and aggregated into rough classes, which can be created manually or generated by unsupervised learning methods.

Suppose $\mathcal{X} = \{X_{\text{cavitation}}, X_{\text{non-cavitation}}\}$ are sample signals from the data space and labels from the space $\mathcal{Y}$. The crucial difference between hierarchical classification and standard classification is that each label $y_i$ has $k$ elements, where $y_i^{(k)}$ denotes the label of the signal at the $k$-th level in the hierarchical multi-label tree. Thus, $\mathcal{Y}^{(0)}$ is defined as the root node and $\mathcal{Y}^{(1)}$ represents a series of child nodes at the first hierarchical level under the root node, which correspond to the roughest class. And $\mathcal{Y}^{(K)} (1 < K \leq N)$ indicates the hierarchical classes that are progressively finer as $K$ increases.

In this research, $\mathcal{Y}^{(1)}$ denotes the coarsest class, i.e. $\mathcal{Y}^{(1)} = \{\text{cavitation, non-cavitation}\}$. $\mathcal{Y}^{(2)}$ denotes the most refined class, i.e. $\mathcal{Y}^{(2)} = \{\text{choked flow, constant, incipient}\}$. In other words, we are attempting to learn a function $\mathcal{F}: \mathcal{X} \rightarrow \mathcal{Y}$, which approximates the true distribution $P(\mathcal{Y}|\mathcal{X})$ of paths in a hierarchical multi-label tree. Each path corresponds to the full label of the signal, e.g. [cavitation, cavitation choked flow], [cavitation, constant cavitation] and [cavitation, incipient cavitation]. Physically impossible paths, e.g. [non cavitation, cavitation choked flow], [non cavitation, constant cavitation] and [non cavitation, incipient cavitation] have a prior probability of 0.

3.6 Experience filtering

Experience filtering is designed to filter dirty and non cavitation data and improve the accuracy of cavitation intensity recognition (see Figure 4). And it focuses on filtering the test data by taking the intersection of the index address of each original test sample and the index address of the cavitation data that has been detected by the sub neural network.

In detail, suppose $I$ denotes the index address of the original test sample from the data space and $\tilde{I}$ represents the index address of the cavitation samples that have been detected by the sub neural network. Therefore, the test sample of cavitation $\tilde{X}$ through operation of the experience filtering is defined as follows:

$$\tilde{X} = \mathcal{X}(I \cap \tilde{I})$$

where, in the best case, the number of samples of $\tilde{X}$ is equal to the number of original test samples of cavitation $X_{\text{cavitation}}$, i.e. $\text{Num}(\tilde{X}) = \text{Num}(X_{\text{cavitation}})$. But in general, the number of samples of $\tilde{X}$ is less than the number of original test samples of cavitation $X_{\text{cavitation}}$, i.e. $\text{Num}(\tilde{X}) < \text{Num}(X_{\text{cavitation}})$. If $\text{Num}(\tilde{X}) = \text{Num}(X_{\text{cavitation}})$, then experience filtering only plays the role of filtering the test samples of non cavitation.

4 Experiments

4.1 Overview

In our experiments, first evaluation metrics are introduced. Then, Dataset 1, Dataset 2 and Dataset 3 of the cavitation intensity recognition are described. And we analyze the effect of the window size $W_{\text{size}}$ of Swin-FFT on the performance of SMTNet. Finally, we compare the performance of SMTNet and other state-of-the-art deep learning and machine learning models on Dataset 1, Dataset 2 and Dataset 3.

In all experiments, we use adaptive moment estimation (Adam) as our optimizer with learning rate set to be $1 \times 10^{-4}$. Both our model and the model of the comparison state-of-the-art method are trained on NVIDIA GPU and the number of training epochs is set to 100 on all datasets. These setting ensures that all trained models are more fairly analyzed for performance comparisons. In addition, both our method and the baseline methods are trained with the same data augmentation (Swin-FFT) in our implementation.

4.2 Evaluation Metrics

In order to evaluate the model after training, four metrics are chosen to comprehensively assess the model performance: Accuracy, Precision, Recall and F1-score. We first calculate the confusion matrix to more conveniently define the evaluation metrics and visualize model performance. In the confusion matrix shown in Figure 6, each column represents the predicted class, and each row represents the actual class. TP (True Positive) is the fraction of positive samples those got correctly predicted by the model, and TN (True Negative) is for the correctly predicted negative samples. FP (False Positive) means the incorrectly classified positive samples those should be negative actually, and FN (False Negative) is for the incorrectly predicted negative samples.
Figure 6: The Confusion Matrix.

Accuracy, Precision, Recall and F1-score are common evaluation metrics for classification problems, defined as:

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (4)
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \quad (5)
\]

\[
F1 - score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)
\]

4.3 Case 1: Dataset 1

4.3.1 Data description

In this subsection, the proposed SMTNet is evaluated on the condition monitoring of cavitation dataset (Dataset 1) provided by SAMSON AG in Frankfurt. The hardware of this experiment is shown in Figure 1 and five flow status are induced in the acoustic signal data by varying the differential pressure at various constant upstream pressures of the control valve different operation conditions: cavitation choked flow, constant cavitation, incipient cavitation, turbulent flow and background no-flow, as shown in Table 1. The turbulent flow and background no-flow are non-cavitation conditions. The experiments have been conducted using seven different valve strokes at four different upstream pressures and the operating parameters are shown in Table 2. Dataset 1 has a total of 356 acoustic signal samples and the frequency of samples is 1562.5 kHz within time duration of 3 sec. It should be noted that the Dataset 1 has been measured by SAMSON AG in a professional environment.

Table 1: Details of the flow status condition of Dataset 1.

| Flow status           | Number of samples |
|-----------------------|-------------------|
| Cavitation            |                   |
| Cavitation choked flow | 72                |
| Constant cavitation   | 93                |
| Incipient cavitation  | 40                |
| Non cavitation        |                   |
| Turbulent flow        | 118               |
| No flow               | 33                |

4.3.2 Results of cavitation detection

The effect of $W_{size}$ on the accuracy of cavitation detection is studied (see Appendix for other metrics). The $W_{size}$ is set to be 2234720, 1167360, 778240, 583680, 466944, 389120, 333531, 291840, 259413 and 233472. The results of cavitation detection of Dataset 1 is shown in Table 3.
Table 2: Operation parameters of *Dataset 1*.

| No. | Valve stroke (mm) | Upstream pressure (bar) | Temperature (°C) |
|-----|-------------------|-------------------------|------------------|
| 1   | 15                | [10,9,6,4]              | 25-50            |
| 2   | 13.5              | [10,9,6,4]              | 25-50            |
| 3   | 11.25             | [10,9,6,4]              | 25-50            |
| 4   | 7.50              | [10,9,6,4]              | 25-50            |
| 5   | 3.75              | [10,9,6,4]              | 25-50            |
| 6   | 1.50              | [10,9,6,4]              | 25-50            |
| 7   | 0.75              | [10,9,6,4]              | 25-50            |

Table 3: Accuracy results of different $W_{size}$ of cavitation detection in *Dataset 1* (%).

| Method                  | Window Size ($W_{size}$) | 2334720 | 1167360 | 778240 | 583680 | 466944 | 389120 | 333531 | 291840 | 259413 | 233472 |
|------------------------|--------------------------|---------|---------|--------|--------|--------|--------|--------|--------|--------|--------|
| SVM [21]               |                          | 81.43   | 82.86   | 80.24  | 79.82  | 83.29  | 79.29  | 79.29  | 80.00  | 80.56  | 79.14  |
| Decision Tree [14]     |                          | 73.57   | 76.07   | 74.29  | 76.96  | 77.00  | 76.55  | 77.86  | 76.07  | 79.44  | 81.86  |
| 1-D CNN [25]           |                          | 94.29   | 94.29   | 94.05  | 94.46  | 94.14  | 95.24  | 94.90  | 95.09  | 95.71  | 95.21  |
| XGBoost + ASFE [49]    |                          | 93.56   | 92.36   | 92.36  | 91.32  | 91.25  | 91.08  | 88.99  | 89.93  | 89.51  | 90.00  |
| 1-D Resnet-18*         |                          | 95.00   | 95.71   | 95.71  | 95.54  | 95.43  | 96.19  | 96.12  | 95.89  | 95.48  | 95.64  |
| SMTNet (our method)    |                          | 96.43   | 96.71   | 96.67  | 96.43  | 96.43  | 97.02  | 96.82  | 96.07  | 96.03  | 96.23  |

* our baseline

From Table 3 it can be seen that SMTNet achieves the best accuracy of 97.02% when $W_{size}$ is 389120. The SMTNet is always better than other methods under the same value of $W_{size}$. And the accuracy of the SMTNet is above 96% at each particular value of $W_{size}$.

4.3.3 Results of cavitation intensity recognition

The impact of $W_{size}$ on the accuracy of cavitation intensity recognition is investigated and is shown in Table 4 and Figure 7 (see Appendix for other metrics).

From Table 4 and Figure 7, it can be observed that the accuracy of SMTNet gradually increases when $2334720 \geq W_{size} \geq 466944$. And SMTNet achieves the best cavitation intensity recognition accuracy of 95.32% when $W_{size}$ is 466944. When $466944 \geq W_{size} \geq 233472$, the accuracy of SMTNet progressively decreases and remains above 93%. The accuracy of SMTNet is improved by 42.82%, 41.88%, 16.07%, 7.55% and 13.32% compared to SVM, Decision Tree, XGBoost (ASFE), 1-D CNN and 1-D ResNet-18, respectively.

To describe the cavitation intensity recognition results in more detail, the confusion matrix of the testing accuracy is shown in Figure 8. It can be seen that the choked flow cavitation and the constant cavitation are most easily to be identified with the highest accuracy compared to the incipient cavitation. This can be explained by the fact that the choked flow cavitation and the constant cavitation have special features that distinguish them from the incipient cavitation [50, 51].

Table 4: Accuracy results of different $W_{size}$ of cavitation intensity recognition in *Dataset 1* (%).

| Method                  | Window Size ($W_{size}$) | 2334720 | 1167360 | 778240 | 583680 | 466944 | 389120 | 333531 | 291840 | 259413 | 233472 |
|------------------------|--------------------------|---------|---------|--------|--------|--------|--------|--------|--------|--------|--------|
| SVM [21]               |                          | 52.50   | 47.50   | 48.75  | 48.13  | 52.00  | 47.29  | 51.61  | 47.97  | 50.56  | 52.25  |
| Decision Tree [14]     |                          | 48.75   | 37.50   | 48.75  | 53.44  | 47.75  | 50.21  | 47.32  | 44.69  | 45.14  | 51.38  |
| 1-D CNN [25]           |                          | 73.75   | 78.75   | 75.42  | 73.75  | 79.25  | 76.46  | 73.93  | 74.38  | 71.81  | 72.25  |
| XGBoost + ASFE [49]    |                          | 86.25   | 85.63   | 87.77  | 81.25  | 82.00  | 83.54  | 80.36  | 81.25  | 81.53  | 82.00  |
| 1-D Resnet-18*         |                          | 76.25   | 79.38   | 77.92  | 79.69  | 82.00  | 81.46  | 81.61  | 80.47  | 80.00  | 79.38  |
| SMTNet (our method)    |                          | 84.93   | 89.80   | 92.41  | 93.33  | 95.32  | 95.12  | 93.93  | 95.03  | 94.12  | 93.48  |
The Size of Sliding Window ($W_{size}$)

Hierarchical Cavitation Intensity Recognition Accuracy (%)

| Method       | SVM     | Decision Tree | XGBoost (ASFE) | 1D CNN | 1D ResNet-18 | SMTNet (our method) |
|--------------|---------|---------------|----------------|--------|--------------|---------------------|
| Dataset 1    |         |               |                |        |              |                     |
| $W_{size}$   |         |               |                |        |              |                     |
| 2334720      | 0.964   | 0.036         | 0.000          |        |              |                     |
| 1167360      | 0.017   | 0.983         | 0.000          |        |              |                     |
| 778240       | 0.000   | 0.154         | 0.846          |        |              |                     |

Figure 7: The effect of $W_{size}$ on cavitation intensity recognition accuracy for SMTNet and comparison methods in Dataset 1.

Figure 8: The confusion matrix for the best cavitation intensity recognition accuracy of the SMTNet in Dataset 1.

4.4 Case 2: Dataset 2

4.4.1 Data description

In this case study, the proposed SMTNet is tested on condition monitoring of cavitation dataset (Dataset 2) provided by SAMSON AG in Frankfurt. The principle of the experimental setup is shown in Figure 1. Dataset 2 uses different valves and sensors compared to Dataset 1. The five flow states are shown in Table 5. The experiments have been conducted using seven different valve strokes at three different upstream pressures and the operating parameters are shown in Table 6. The amount of Dataset 2 is 806 and the frequency of samples is 1562.5 kHz within time duration of 25 sec. It should be noticed that the Dataset 2 has been collected by SAMSON AG in a professional environment.

4.4.2 Results of cavitation detection

The effect of $W_{size}$ on the accuracy of cavitation detection is investigated (see Appendix of other metrics). The $W_{size}$ is set to be 2234720, 1167360, 778240, 583680 and 466944. The comparison results of cavitation detection of Dataset 2 is shown in Table 7.

From Table 7, it can be noted that SMTNet achieves the best accuracy of 97.67% when $W_{size}$ is 778240. And SMTNet has the better accuracy compared to other methods under the same value of $W_{size}$. And the accuracy of the SMTNet is above 96% at each particular value of $W_{size}$.
Table 5: Details of the flow status condition of Dataset 2.

| Flow status          | Number of samples |
|----------------------|-------------------|
| Cavitation choked flow| 148               |
| Constant cavitation  | 396               |
| Incipient cavitation | 64                |
| Non cavitation       |                   |
| Turbulent flow       | 183               |
| No flow              | 15                |

Table 6: Operation parameters of Dataset 2.

| No. | Valve stroke (mm) | Upstream pressure (bar(a)) | Temperature (°C) |
|-----|-------------------|-----------------------------|------------------|
| 1   | 60                | [10,6,4]                    | 23-52            |
| 2   | 55                | [10,6,4]                    | 23-52            |
| 3   | 45                | [10,6,4]                    | 23-52            |
| 4   | 30                | [10,6,4]                    | 23-52            |
| 5   | 25                | [10,6,4]                    | 23-52            |
| 6   | 15                | [10,6,4]                    | 23-52            |
| 7   | 6                 | [10,6,4]                    | 23-52            |

4.4.3 Results of cavitation intensity recognition

The affect of $W_{size}$ on the accuracy of cavitation intensity recognition is investigated (see Appendix of other metrics). The comparison accuracy of cavitation intensity recognition of Dataset 2 are shown in Table 8 and Figure 9.

From Table 5, it can be found that SMTNet gets the best cavitation intensity recognition accuracy of 97.16% when $W_{size}$ is 778240. The accuracy of SMTNet gradually increases when $2334720 \geq W_{size} \geq 778240$. When $778240 > W_{size} \geq 466944$, the accuracy of SMTNet progressively decreases and remains above 95%. The best cavitation intensity recognition of results from the SVM, Decision Tree, XGBoost (ASFE), 1-D CNN and 1-D Resnet-18 are 46.88%, 67.11%, 92.84%, 92.50% and 93.32%, respectively, which were improved by 50.28%, 30.05%, 4.32%, 4.66% and 3.84% compared to SMTNet. As can be seen from Figure 9, SMTNet has achieved with higher accuracy than all other approaches at each particular value of $W_{size}$.

The results of cavitation intensity recognition in more detail, the confusion matrix for the best testing accuracy is shown in Figure 10. It can be noted that choked flow cavitation and constant cavitation are most easily identified with the highest accuracy compared to the incipient cavitation. And the accuracy of the choked flow cavitation and the constant cavitation can reach 100% and 98.3%, respectively.

Table 7: Accuracy results of different $W_{size}$ of cavitation detection in Dataset 2 (%).

| Method                        | Window Size ($W_{size}$) |
|-------------------------------|---------------------------|
| SVM [21]                      | 2334720 1167360 778240 583680 466944 |
| Decision Tree [14]            | 89.83 89.36 89.06 89.92 89.30 |
| 1-D CNN [25]                  | 89.58 88.59 89.96 89.84 88.97 |
| XGBoost + ASFE [49]           | 94.29 95.24 94.05 94.46 94.14 |
| 1-D Resnet-18 + ASFE [49]     | 90.56 90.73 91.33 91.02 90.43 |
| SMTNet (our method)           | 95.48 96.19 95.71 95.54 95.43 |
| SMTNet (our method)           | 96.67 97.02 97.67 96.43 96.43 |
Table 8: Accuracy results of different $W_{size}$ of cavitation intensity recognition in Dataset 2 (\%).

| Method                          | Window Size ($W_{size}$) |
|---------------------------------|--------------------------|
|                                 | 2334720                  |
|                                 | 1167360                  |
|                                 | 778240                   |
|                                 | 583680                   |
|                                 | 466944                   |
| SVM [21]                        | 46.88                    |
| Decision Tree [14]              | 67.11                    |
| 1-D CNN [25]                   | 90.63                    |
| XGBoost + ASFE [49]             | 89.97                    |
| 1-D Resnet-18 $^*$              | 91.61                    |
| SMTNet (our method)             | 93.91                    |

The Size of Sliding Window ($W_{size}$)

40 60 80 100

Hierarchical Cavitation Intensity Recognition Accuracy (%)

SVM  Decision Tree  XGBoost (ASFE)  1D CNN  1D ResNet-18  SMTNet (our method)

2334720 1167360 778240 583680 466944

Figure 9: The effect of $W_{size}$ on cavitation intensity recognition accuracy for SMTNet and comparison methods in Dataset 2.

Figure 10: The confusion matrix for the best cavitation intensity recognition accuracy of the SMTNet in Dataset 2.
4.5 Case 3: Dataset 3

4.5.1 Data description

During this case research, the proposed SMTNet is evaluated on condition monitoring of cavitation dataset (Dataset 3) provided by SAMSON AG in Frankfurt. Dataset 3 is different from Dataset 1 and Dataset 2 by carrying the noise of the real environment. The five flows states about Dataset 3 are shown in Table 9. The experimental operational parameters about Dataset 3 are shown in Table 10. The quantity of Dataset 3 is 160 and the frequency of samples is 1562.5 kHz within time duration of 25 sec. It should be pointed out that the Dataset 3 has been collected by SAMSON AG inside a professional environment.

4.5.2 Results of cavitation detection

The influence of $W_{size}$ on the accuracy of cavitation detection is researched (see Appendix of other metrics). The $W_{size}$ is the same as the $W_{size}$ of Dataset 2. The accuracy of cavitation detection of Dataset 3 is shown in Table 11. As can be seen from Table 11, SMTNet and comparative methods have achieved 100% accuracy during each of the $W_{size}$. It can be concluded that the cavitation and non cavitation features of Dataset 3 are more easily distinguished compared to Dataset 1 and Dataset 2.

4.5.3 Results of cavitation intensity recognition

The impact of $W_{size}$ on the accuracy of cavitation intensity recognition is investigated and is shown in Table 12 and Figure 11 (see Appendix of other metrics). As can be seen from Table 12 and Figure 11, the accuracy of SMTNet and the comparison method (except SVM [21]) achieved 100% for each specific $W_{size}$. And our method has achieved 100% accuracy of recognition of all cavitation state (see Figure 12).

The reasons why our method and compared methods for cavitation detection and cavitation intensity recognition have achieved excellent results of Dataset 3 compared to Dataset 1 and Dataset 2 are as follows. First, although Dataset 3

| Flow status               | Number of samples |
|---------------------------|-------------------|
| Cavitation choked flow    | 40                |
| Cavitation                | Constant cavitation 40 |
|                           | Incipient cavitation 40 |
| Non cavitation            | Turbulent flow    | 40                |

Table 10: Operation parameters of Dataset 3.

| No. | Valve stroke (mm) | Upstream pressure (bar(a)) | Temperature (°C) |
|-----|-------------------|-----------------------------|------------------|
| 1   | 15                | 10                          | 32-39            |

Table 11: Accuracy results of different $W_{size}$ of cavitation detection in Dataset 3 (%).

| Method               | Window Size ($W_{size}$) |
|----------------------|---------------------------|
| SVM [21]             | 2334720 1167360 778240 583680 466944 |
| Decision Tree [14]   | 100.00 100.00 100.00 100.00 100.00 |
| 1-D CNN [25]         | 100.00 100.00 100.00 100.00 100.00 |
| XGBoost + ASFE [49]  | 100.00 100.00 100.00 100.00 100.00 |
| 1-D Resnet-18°        | 100.00 100.00 100.00 100.00 100.00 |
| SMTNet (our method)  | 100.00 100.00 100.00 100.00 100.00 |
Table 12: Accuracy results of different $W_{size}$ of cavitation intensity recognition in Dataset 3 (%).

| Method                 | Window Size ($W_{size}$) |
|------------------------|--------------------------|
|                        | 2334720 1167360 778240 583680 466944 |
| SVM [21]               | 44.08 45.96 46.25 49.12 51.30 |
| Decision Tree [14]     | 100.00 100.00 100.00 100.00 100.00 |
| 1-D CNN [25]           | 100.00 100.00 100.00 100.00 100.00 |
| XGBoost + ASFE [49]    | 100.00 100.00 100.00 100.00 100.00 |
| 1-D Resnet-18°         | 100.00 100.00 100.00 100.00 100.00 |
| SMTNet (our method)    | 100.00 100.00 100.00 100.00 100.00 |

Figure 11: The effect of $W_{size}$ on cavitation intensity recognition accuracy for SMTNet and comparison methods in Dataset 3.

Figure 12: The confusion matrix for the best cavitation intensity recognition accuracy of the SMTNet in Dataset 3.
Table 13: The overall cavitation intensity recognition results of the SMTNet and the results of comparison methods are in Dataset 1, Dataset 2 and Dataset 3 (%).

| Data       | Method               | Accuracy | Overall  |
|------------|----------------------|----------|----------|
|            |                      | Incipient cavitation |          |
|            | SVM [21]             | 20.53    | 68.71    |
|            | Decision Tree [14]   | 11.81    | 54.84    |
|            | 1-D CNN [25]         | 53.15    | 87.14    |
| **Dataset 1** | XGBoost + ASFE [49] | 53.30    | 87.22    |
|            | 1-D Resnet-18*       | 52.78    | 85.86    |
|            | 1-D DHRN**           | 60.90    | 93.75    |
|            | SMTNet               | **68.75**| **93.85**|
|            | SVM [21]             | 59.38    | 50.49    |
|            | Decision Tree [14]   | 67.00    | 65.07    |
|            | 1-D CNN [25]         | 72.50    | 86.13    |
| **Dataset 2** | XGBoost + ASFE [49] | 76.33    | 89.22    |
|            | 1-D Resnet-18*       | 78.33    | 91.71    |
|            | 1-D DHRN**           | 79.17    | 94.31    |
|            | SMTNet               | **92.83**| **95.53**|
|            | SVM [21]             | 31.02    | 56.70    |
|            | Decision Tree [14]   | 42.47    | 63.28    |
|            | 1-D CNN [25]         | 99.75    | 99.44    |
| **Dataset 3** | XGBoost + ASFE [49] | 68.19    | 83.79    |
|            | 1-D Resnet-18*       | 99.85    | 99.96    |
|            | 1-D DHRN**           | **100.00**| **100.00**|
|            | SMTNet               | **100.00**| **100.00**|

** our baseline  *** our previous research

with real background noise compared to Dataset 1 and Dataset 2, our data augmentation of the Swin-FFT operation can filter most of the noise. Second, Dataset 3 are obtained with only one operating of valve stroke and upstream pressure (see Table 10). Third, Dataset 3 is balanced for each cavitation state (see Table 9). For a more specific analysis of the above reasons, see our previous research. From the above, we can infer that different valve openings and upstream pressures can affect the accuracy of cavitation detection and cavitation intensity recognition.

5 Discussions

5.1 Overall results

The overall results of cavitation intensity recognition is an overall calculation of the results of the cavitation detection and hierarchical cavitation intensity recognition, i.e. the result of the four-class classification. In this case, we only show the overall cavitation intensity recognition results corresponding to the best hierarchical cavitation intensity recognition results of the SMTNet (the comparison methods are the best result for the four-class classification), as shown in Table 13.

From Table 13, it can be seen that the accuracy of SMTNet for overall cavitation intensity recognition in Dataset 1, Dataset 2 and Dataset 3 is 93.85%, 95.53% and 100%, respectively. The accuracy of cavitation intensity recognition by SMTNet improved by 7.99%, 3.82% and 0.01% compared to 1-D ResNet-18 with direct four-class classification in Dataset 1, Dataset 2 and Dataset 3, respectively. And the accuracy of SMTNet for the most difficult to recognize the incipient cavitation state is 68.75%, 92.83% and 100% in Dataset 1, Dataset 2 and Dataset 3, respectively. This can indicate that our hierarchical cavitation intensity recognition method (SMTNet) can improve not only the overall accuracy, but also the accuracy of the incipient cavitation state.
5.2 Analysis of different frequencies of samples

In practical applications, the level of sensors represent the quality of the data obtained. The ability to recognize different levels of cavitation intensity with the data obtained from low level sensors becomes very significant and challenging. In this research, SMTNet is evaluated for hierarchical cavitation intensity recognition and cavitation detection under the original frequency of samples ($F_s = 1562500$ Hz), one-half, one-quarter, one-sixth, one-eighth of the original frequency of samples ($781250$ Hz, $390625$ Hz, $260416$ Hz and $195312$ Hz) and the highest frequency of samples of the mobile phone ($48000$ Hz ≈ $F_s/32$), respectively. The hierarchical cavitation intensity recognition and cavitation detection accuracy of the SMTNet model has been compared again in Dataset 1, Dataset 2 and Dataset 3 with different frequencies of samples, as shown in Figure 13.

- **Dataset 1 and Dataset 2.** For hierarchical intensity recognition, although the SMTNet model begins to suffer from gradual reduction in accuracy as the frequency of samples decreases, the accuracy always always remains above 84% when $1562500$ Hz ≥ $F_s$ ≥ $195312$ Hz. And SMTNet has achieved 75.88% and 79.34% accuracy when the frequency of samples is equal to $48000$ Hz (32nd of the original signal frequency of samples) in Dataset 1 and Dataset 2, respectively. For cavitation detection, the accuracy of the SMTNet model progressively decreases as the frequency of samples decreases, but the accuracy of cavitation detection remains above 93% at each particular value of sampling frequency. When the frequency of samples is equal to $48000$ Hz, the SMTNet has obtained 93.29% and 93.57%, respectively. And when the frequency of samples is reduced to one-32nd of the original signal frequency of samples, the accuracy of SMTNet only decreased by 3.73% and 4.07%.

- **Dataset 3.** For hierarchical intensity recognition, the accuracy of SMTNet begins to reduce when the frequency of sample is $260416$ Hz ($260416$ Hz ≈ $F_s/6$). The accuracy of SMTNet always remains above 98% when $260416$ Hz ≥ $F_s$ ≥ $195312$ Hz. And our method has achieved 97.44% accuracy when the frequency of sample is equal to $48000$ Hz. For cavitation detection, the accuracy of our method always remains above 99% at each particular value of $F_s$. When the frequency of samples is equal to $48000$ Hz, our method obtains 99.28%, which is reduced by only 0.72% of the accuracy when compared to the original frequency of samples.
6 Conclusion and Feature Research

In this research, we proposed a novel two-step framework using hierarchy transfer learning and the hierarchical multi-label tree to build deep learning models for cavitation detection and cavitation intensity recognition based on an analysis of the process of detecting cavitation by engineers. Compared with traditional machine learning and CNN models, the SMTNet can output multiple hierarchical predictions from coarse to fine, which is more informative and interpretable. To the best of our knowledge, besides to be the first deep learning framework for hierarchical cavitation intensity recognition, other main contributions to this paper are summarized as the following five points. Firstly, a sliding window with fast fourier transform (Swin-FFT) data augmentation method is introduced to solve the few-short learning problem. Secondly, the 1-D double hierarchical residual blocks (1-D DHRB) with large kernel is proposed as a feature extractor to capture sensitive features of valves acoustics signals. Thirdly, the hierarchical transfer learning and the hierarchical multi-label tree are proposed for building deep learning models for hierarchical cavitation intensity recognition. Fourthly, an experience filtering mechanism is proposed to make greater use of the a priori knowledge of cavitation detection. Finally, the SMTNet has been evaluated on three dataset of valve acoustic signals and has achieved significant results of cavitation detection and cavitation intensity recognition. Moreover, the SMTNet has also been tested during different frequencies of samples and has achieved excellent results of the highest frequency of samples of mobile phones. These results have demonstrated the effectiveness of the proposed novel two-step hierarchical cavitation intensity recognition framework in the field of intelligent cavitation detection. At the same time, the research provides the possibility of learning with other structured outputs, such as linear chains or graphs.

The limitations of the proposed method may include the following aspects. Firstly, the proposed method has low accuracy of the incipient cavitation. Secondly, the proposed approach is the two-step hierarchical detection framework. Therefore, based on the above limitations, the future researches should be done in the following way. Firstly, the method could be further modified to improve the accuracy of the incipient cavitation. Secondly, the proposed method could be modified to one-step hierarchical detection framework.

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References

[1] A Masjedian Jazi and H Rahimzadeh. Detecting cavitation in globe valves by two methods: Characteristic diagrams and acoustic analysis. Applied Acoustics, 70(11-12):1440–1445, 2009.
[2] Rui Zhao, Rong-qing Xu, Zhong-hua Shen, Jian Lu, and Xiao-wu Ni. Experimental investigation of the collapse of laser-generated cavitation bubbles near a solid boundary. Optics & Laser Technology, 39(5):968–972, 2007.
[3] Ahmed Ramadhan Al-Obaidi. Detection of cavitation phenomenon within a centrifugal pump based on vibration analysis technique in both time and frequency domains. Experimental Techniques, 44(3):329–347, 2020.
[4] EA Brujan, GS Keen, A Vogel, and JR Blake. The final stage of the collapse of a cavitation bubble close to a rigid boundary. Physics of fluids, 14(1):85–92, 2002.
[5] Marion Bonnier and Olivier Eiff. Experimental investigation of the collapse of a turbulent wake in a stably stratified fluid. Physics of fluids, 14(2):791–801, 2002.
[6] QN Song, YG Zheng, DR Ni, and ZY Ma. Corrosion and cavitation erosion behaviors of friction stir processed ni-al bronze: effect of processing parameters and position in the stirred zone. Corrosion, 70(3):261–270, 2014.
[7] Kristoffer McKee, Gareth Forbes, Muhammad Ilyas Mazhar, Rodney Entwistle, and Ian Howard. A review of major centrifugal pump failure modes with application to the water supply and sewerage industries. In ICOMS Asset Management Conference Proceedings. Asset Management Council, 2011.
[8] C Schleihs, E Vienmet, M Deeken, H Ding, Y Xia, S Lowry, and H Murrenhoff. 3d-cfd simulation of an axial piston displacement unit. In Ninth International Fluid Power Conference, Aachen, Germany, Mar, pages 24–26, 2014.
[9] Fang-long Yin, Song-lin Nie, Shu-han Xiao, and Wei Hou. Numerical and experimental study of cavitation performance in sea water hydraulic axial piston pump. *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, 230(8):716–735, 2016.

[10] Christopher E Brennen. *Cavitation and bubble dynamics*. Cambridge University Press, 2014.

[11] Hossein Gholizadeh, Richard Burton, and Greg Schoenau. Fluid bulk modulus: comparison of low pressure models. *International journal of fluid power*, 13(1):7–16, 2012.

[12] Y Liu, J Lin, TA Dean, and DC J Farrugia. A numerical and experimental study of cavitation in a hot tensile axisymmetric testpiece. *The Journal of strain analysis for engineering design*, 40(6):571–586, 2005.

[13] Brad Clarke and Kari Oksanen. Evaluating cavitation solutions—past and present. *Opflow*, 37(7):18–23, 2011.

[14] NR Sakhivel, V Sugumaran, and SJESWa Babudevasenapati. Vibration based fault diagnosis of monoblock centrifugal pump using decision tree. *Expert Systems with Applications*, 37(6):4040–4049, 2010.

[15] J Ross Quinlan. *C4. 5: programs for machine learning*. Elsevier, 2014.

[16] V Muralidharan and V Sugumaran. Feature extraction using wavelets and classification through decision tree algorithm for fault diagnosis of mono-block centrifugal pump. *Measurement*, 46(1):353–359, 2013.

[17] Raghuvir Rao. Wavelet transforms. *Encyclopedia of imaging science and technology*, 2002.

[18] V Muralidharan, V Sugumaran, and V Indira. Fault diagnosis of monoblock centrifugal pump using svm. *Engineering Science and Technology, an International Journal*, 17(3):152–157, 2014.

[19] BISWAJJIT Samanta, KR Al-Balushi, and SA Al-Araimi. Artificial neural networks and support vector machines with genetic algorithm for bearing fault detection. *Engineering applications of artificial intelligence*, 16(7-8):657–665, 2003.

[20] John H Holland. Genetic algorithms. *Scientific american*, 267(1):66–73, 1992.

[21] Bo-Suk Yang, Won-Woo Hwang, Myung-Han Ko, and Soo-Jong Lee. Cavitation detection of butterfly valve using support vector machines. *Journal of sound and vibration*, 287(1-2):25–43, 2005.

[22] DJ Bordoloi and Rajiv Tiwari. Identification of suction flow blockages and casing cavitations in centrifugal pumps by optimal support vector machine techniques. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 39(8):2957–2968, 2017.

[23] Asish Kumar Panda, Janani Shruti Rapur, and Rajiv Tiwari. Prediction of flow blockages and impending cavitation in centrifugal pumps using support vector machine (svm) algorithms based on vibration measurements. *Measurement*, 130:44–56, 2018.

[24] Janani Shruti Rapur and Rajiv Tiwari. Automation of multi-fault diagnosing of centrifugal pumps using multi-class support vector machine with vibration and motor current signals in frequency domain. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 40(6):1–21, 2018.

[25] Mohammad Taghi Shervani-Tabar, Mir Mohammad Ettefagh, Saeed Lotfan, and Hamed Safarzadeh. Cavitation intensity monitoring in an axial flow pump based on vibration signals using multi-class support vector machine. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 232(17):3013–3026, 2018.

[26] Rafik Zouari, Sophie Sieg-Zieba, and Menad Sidahmed. Fault detection system for centrifugal pumps using neural networks and neuro-fuzzy techniques. *Surveillance*, 5:11–13, 2004.

[27] S Rajakarunakaran, P Venkumar, D Devaraj, and K Surya Prakasa Rao. Artificial neural network approach for fault detection in rotary system. *Applied Soft Computing*, 8(1):740–748, 2008.

[28] D Siano and MA Panza. Diagnostic method by using vibration analysis for pump fault detection. *Energy Procedia*, 148:10–17, 2018.

[29] MR Nasiri, MJ Mahjoob, and H Vahid-Alizadeh. Vibration signature analysis for detecting cavitation in centrifugal pumps using neural networks. In *2011 IEEE International Conference on Mechatronics*, pages 632–635. IEEE, 2011.

[30] Rajiv Tiwari, DJ Bordoloi, and Aakash Dewangan. Blockage and cavitation detection in centrifugal pumps from dynamic pressure signal using deep learning algorithm. *Measurement*, 173:108676, 2021.

[31] Primož Potočnik, Borja Olmos, Lučka Vodopivec, Egon Susič, and Edvard Govekar. Condition classification of heating systems valves based on acoustic features and machine learning. *Applied Acoustics*, 174:107736, 2021.

[32] Wanlin Zhao, Zili Wang, Chen Lu, Jian Ma, and Lianfeng Li. Fault diagnosis for centrifugal pumps using deep learning and softmax regression. In *2016 12th world congress on intelligent control and automation (WCICA)*, pages 165–169. IEEE, 2016.
[33] Feng Jia, Yaguo Lei, Jing Lin, Xin Zhou, and Na Lu. Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. *Mechanical Systems and Signal Processing*, 72:303–315, 2016.

[34] Shahab Pasha, Christian Ritz, David Stirling, Paul Zulli, David Pinson, and Sheng Chew. A deep learning approach to the acoustic condition monitoring of a sintering plant. In *2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, pages 1803–1809. IEEE, 2018.

[35] Qun Chao, Jianfeng Tao, Xiaoliang Wei, Yuanhang Wang, Linghui Meng, and Chengliang Liu. Cavitation intensity recognition for high-speed axial piston pumps using 1-d convolutional neural networks with multi-channel inputs of vibration signals. *Alexandria Engineering Journal*, 59(6):4463–4473, 2020.

[36] Long Wen, Xinyu Li, and Liang Gao. A transfer convolutional neural network for fault diagnosis based on resnet-50. *Neural Computing & Applications*, 32(10), 2020.

[37] Serkan Kiranyaz, Turker Ince, and Moncef Gabbouj. Real-time patient-specific eeg classification by 1-d convolutional neural networks. *IEEE Transactions on Biomedical Engineering*, 63(3):664–675, 2015.

[38] Roneel V Sharan and Shlomo Berkovisky. Epileptic seizure detection using multi-channel eeg wavelet power spectra and 1-d convolutional neural networks. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 545–548. IEEE, 2020.

[39] Turker Ince, Serkan Kiranyaz, Levent Eren, Murat Askar, and Moncef Gabbouj. Real-time motor fault detection by 1-d convolutional neural networks. *IEEE Transactions on Industrial Electronics*, 63(11):7067–7075, 2016.

[40] Wei Zhang, Chuanhao Li, Gaoliang Peng, Yuanhang Chen, and Zhujun Zhang. A deep convolutional neural network with new training methods for bearing fault diagnosis under noisy environment and different working load. *Mechanical Systems and Signal Processing*, 100:439–453, 2018.

[41] Feng Jia, Yaguo Lei, Na Lu, and Saibo Xing. Deep normalized convolutional neural network for imbalanced fault classification of machinery and its understanding via visualization. *Mechanical Systems and Signal Processing*, 110:349–367, 2018.

[42] Venkat Venkatasubramanian, Raghunathan Rengaswamy, and Surya N Kavuri. A review of process fault detection and diagnosis: Part ii: Qualitative models and search strategies. *Computers & Chemical Engineering*, 27(3):313–326, 2003.

[43] Carlos N Silla and Alex A Freitas. A survey of hierarchical classification across different application domains. *Data Mining and Knowledge Discovery*, 22(1):31–72, 2011.

[44] Alexandra L’heureux, Katarina Grolinger, Hany F Elyamany, and Miriam AM Capretz. Machine learning with big data: Challenges and approaches. *IEEE Access*, 5:7776–7797, 2017.

[45] Connor Shorten and Taghi M Khoshgoftaar. A survey on image data augmentation for deep learning. *Journal of Big Data*, 6(1):1–48, 2019.

[46] Long-Gang Pang, Kai Zhou, Nan Su, Hannah Petersen, Horst Stöcker, and Xin-Nian Wang. An equation-of-state-meter of quantum chromodynamics transition from deep learning. *Nature Commun.*, 9(1):210, 2018.

[47] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

[48] Marina Sokolova and Guy Lapalme. A systematic analysis of performance measures for classification tasks. *Information processing & management*, 45(4):347–377, 2009.

[49] Yu Sha, Johannes Faber, Shuiping Gou, Bo Liu, Wei Li, Stefan Schramm, Horst Stoecker, Thomas Steckenreiter, Domagoj Vnucce, Nadine Wetzstein, Andreas Widl, and Kai Zhou. An acoustic signal cavitation detection framework based on xgboost with adaptive selection feature engineering. *Measurement*, 192:110897, 2022.

[50] AF Lehman and JO Young. Experimental investigations of incipient and desinent cavitation. *Journal of Basic Engineering*, pages 275–284, 1964.

[51] Pietro Marani, Massimo Martelli, Cesare Dolcin, and Silvia Gessi. Orifices flow saturation in oil hydraulic applications.
Appendix A

Examples of cavitation states

Figures A1, A2 and A3 show examples of different cavitation states for Dataset 1, Dataset 2 and Dataset 3, respectively.

Hierarchical cavitation intensity recognition

The precision, recall and F1-score of the SMTNet (our method) and compared methods in Dataset 1, Dataset 2 and Dataset 3 are shown in Table A1, Table A2 and A3.

Cavitation Detection

The precision, recall and F1-score of the SMTNet (our method) and compared methods in Dataset 1, Dataset 2 and Dataset 3 are shown in Table A4, Table A5 and A6.

The accuracy of the SMTNet (our method) and comparison methods during different $W_{\text{size}}$ in Dataset 1, Dataset 2 and Dataset 3 are shown in Figures A4, A5 and A6. The confusion probability matrix of our method for best accuracy in Dataset 1, Dataset 2 and Dataset 3 are shown in Figures A7, A8 and A9.

Downsampling analysis

The accuracy, precision, recall and F1-scores of the SMTNet for cavitation detection during different frequencies of samples in Dataset 1, Dataset 2 and Dataset 3 are shown in Table A7.

The accuracy, precision, recall and F1-scores of the SMTNet for cavitation intensity recognition during different frequencies of samples in Dataset 1, Dataset 2 and Dataset 3 are shown in Table A8.
Figure A2: Examples of (a)-(d) for cavitation choked flow, constant cavitation, incipient cavitation and non-cavitation in Dataset 2.

Figure A3: Examples of (a)-(d) for cavitation choked flow, constant cavitation, incipient cavitation and non-cavitation in Dataset 3.
Table A1: Precision, Recall and F1-score results of different $W_{size}$ of the SMTNet and comparison methods for cavitation intensity recognition in Dataset 1 (%).

| Method          | Window Size ($W_{size}$) | 2334720 | 1167360 | 778240 | 583680 | 466944 | 389120 | 333531 | 291840 | 259413 | 2334720 |
|-----------------|--------------------------|---------|---------|--------|--------|--------|--------|--------|--------|--------|---------|
| SVM [21]        |                          | 57.14   | 58.94   | 45.78  | 51.86  | 54.97  | 46.26  | 52.93  | 46.57  | 56.44  | 45.37   |
| Decision Tree [14] |                        | 64.55   | 38.53   | 51.29  | 61.92  | 40.24  | 67.07  | 49.11  | 51.84  | 56.94  | 49.99   |
| 1-D CNN [25]    |                          | 66.46   | 75.32   | 38.12  | 75.77  | 86.68  | 80.63  | 49.44  | 76.52  | 74.52  | 74.55   |
| XGBoost + ASFE [49] |                     | 86.38   | 87.86   | 90.46  | 82.25  | 85.29  | 86.03  | 81.14  | 84.65  | 82.66  | 84.87   |
| 1-D Resnet-18* |                          | 83.77   | 85.66   | 82.69  | 80.49  | 83.75  | 85.69  | 83.89  | 83.87  | 81.92  | 82.79   |
| SMTNet          |                          | 84.35   | 92.43   | 94.00  | 94.99  | 96.67  | 96.52  | 95.26  | 96.03  | 93.98  | 94.84   |

| Method          | Window Size ($W_{size}$) | 264       | 1167360 | 778240 | 583680 | 466944 | 389120 | 333531 | 291840 | 259413 | 2334720 |
|-----------------|--------------------------|---------|---------|--------|--------|--------|--------|--------|--------|--------|---------|
| SVM [21]        |                          | 47.20   | 37.45   | 39.58  | 37.53  | 44.45  | 36.07  | 43.23  | 37.95  | 40.35  | 45.96   |
| Decision Tree [14] |                        | 44.35   | 34.67   | 42.89  | 48.51  | 42.22  | 44.21  | 42.13  | 41.76  | 42.34  | 45.64   |
| 1-D CNN [25]    |                          | 66.40   | 73.58   | 68.11  | 73.77  | 74.68  | 73.84  | 61.98  | 77.74  | 76.88  | 77.29   |
| XGBoost + ASFE [49] |                     | 86.25   | 85.63   | 86.67  | 81.25  | 82.00  | 83.54  | 80.36  | 81.25  | 81.52  | 82.00   |
| 1-D Resnet-18* |                          | 73.15   | 73.21   | 74.59  | 77.41  | 79.57  | 79.75  | 74.30  | 79.12  | 76.09  | 72.02   |
| SMTNet          |                          | 79.99   | 89.11   | 91.67  | 92.64  | 93.13  | 93.08  | 94.14  | 94.18  | 90.96  | 92.09   |

Table A2: Precision, Recall and F1-score results of different $W_{size}$ of the SMTNet and comparison methods for cavitation intensity recognition in Dataset 2 (%).

| Method          | Window Size ($W_{size}$) | 2334720 | 1167360 | 778240 | 583680 | 466944 | 389120 | 333531 | 291840 | 259413 | 2334720 |
|-----------------|--------------------------|---------|---------|--------|--------|--------|--------|--------|--------|--------|---------|
| SVM [21]        |                          | 46.09   | 45.61   | 41.57  | 44.90  | 44.59  | 44.89  | 44.49  | 44.60  | 44.99  | 44.59   |
| Decision Tree [14] |                        | 67.07   | 64.52   | 61.98  | 60.89  | 59.51  | 60.51  | 60.31  | 59.76  | 60.85  | 59.35   |
| 1-D CNN [25]    |                          | 90.52   | 91.97   | 92.83  | 92.08  | 92.30  | 92.08  | 92.30  | 92.30  | 92.30  | 92.30   |
| XGBoost + ASFE [49] |                     | 89.91   | 90.64   | 91.42  | 92.39  | 92.42  | 92.42  | 92.42  | 92.42  | 92.42  | 92.42   |
| 1-D Resnet-18* |                          | 91.70   | 92.28   | 93.28  | 93.03  | 92.78  | 93.03  | 92.78  | 92.78  | 92.78  | 92.78   |
| SMTNet          |                          | 94.02   | 95.64   | 97.25  | 96.00  | 95.99  | 96.00  | 95.99  | 95.99  | 95.99  | 95.99   |

| Method          | Window Size ($W_{size}$) | 47.45   | 46.76   | 43.42  | 45.90  | 45.60  | 45.90  | 45.60  | 45.60  | 45.60  | 45.60   |
|-----------------|--------------------------|---------|---------|--------|--------|--------|--------|--------|--------|--------|---------|
| SVM [21]        |                          | 67.01   | 64.43   | 62.06  | 60.85  | 59.35  | 60.85  | 59.35  | 59.35  | 59.35  | 59.35   |
| Decision Tree [14] |                        | 90.49   | 91.76   | 92.85  | 92.14  | 92.17  | 92.14  | 92.17  | 92.17  | 92.17  | 92.17   |
| 1-D CNN [25]    |                          | 89.84   | 90.45   | 91.35  | 92.44  | 92.29  | 92.29  | 92.29  | 92.29  | 92.29  | 92.29   |
| XGBoost + ASFE [49] |                     | 91.53   | 92.08   | 93.31  | 93.06  | 92.69  | 93.06  | 92.69  | 92.69  | 92.69  | 92.69   |
| 1-D Resnet-18* |                          | 93.92   | 95.65   | 97.05  | 95.65  | 95.75  | 95.65  | 95.75  | 95.75  | 95.75  | 95.75   |
| SMTNet          |                          | 93.90   | 95.59   | 97.11  | 95.74  | 95.82  | 95.74  | 95.82  | 95.82  | 95.82  | 95.82   |
Table A3: Precision, Recall and F1-score results of different $W_{size}$ of the SMTNet and comparison methods for cavitation intensity recognition in Dataset 3 (\%).

| Method                  | Window Size ($W_{size}$) |
|-------------------------|--------------------------|
|                         | 2334720 | 1167360 | 778240 | 583680 | 466944 |
| SVM [21]                |         |         |        |        |        |
| Decision Tree [14]      | 92.59   | 88.41   | 88.30  | 90.51  | 99.29  |
| 1-D CNN [25]           | 94.64   | 94.17   | 93.95  | 95.14  | 94.66  |
| XGBoost + ASFE [49]     | 93.14   | 92.61   | 92.48  | 91.63  | 91.57  |
| 1-D Resnet-18*         | 94.72   | 95.63   | 95.45  | 95.26  | 95.59  |
| SMTNet                  | 96.15   | 96.55   | 96.45  | 96.16  | 96.19  |

| SVM [21]                | 73.61   | 73.37   | 71.95  | 70.82  | 73.40  |
| Decision Tree [14]      | 92.59   | 88.41   | 88.30  | 90.51  | 99.29  |
| 1-D CNN [25]           | 94.64   | 94.17   | 93.95  | 95.14  | 94.66  |
| XGBoost + ASFE [49]     | 93.14   | 92.61   | 92.48  | 91.63  | 91.57  |
| 1-D Resnet-18*         | 94.72   | 95.63   | 95.45  | 95.26  | 95.59  |
| SMTNet                  | 96.15   | 96.55   | 96.45  | 96.16  | 96.19  |

Table A4: Precision, Recall and F1-score results of different $W_{size}$ of the SMTNet and comparison methods for cavitation detection in Dataset 1 (\%).

| Method                  | Window Size ($W_{size}$) |
|-------------------------|--------------------------|
|                         | 2334720 | 1167360 | 778240 | 583680 | 466944 | 389120 | 333531 | 291840 | 259413 | 233472 |
| SVM [21]                |         |         |        |        |        |        |        |        |        |        |
| Decision Tree [14]      | 73.61   | 73.37   | 71.95  | 70.82  | 73.40  | 69.87  | 69.62  | 70.85  | 72.38  | 79.15  |
| 1-D CNN [25]           | 92.59   | 88.41   | 88.30  | 90.51  | 99.29  | 89.00  | 98.56  | 84.42  | 97.31  | 92.61  |
| XGBoost + ASFE [49]     | 93.14   | 92.61   | 92.48  | 91.63  | 91.57  | 91.83  | 89.26  | 90.28  | 90.83  | 90.29  |
| 1-D Resnet-18*         | 94.72   | 95.63   | 95.45  | 95.26  | 95.59  | 95.91  | 95.85  | 95.63  | 95.29  | 95.37  |
| SMTNet                  | 96.15   | 96.55   | 96.45  | 96.16  | 96.19  | 96.75  | 96.58  | 96.02  | 96.05  | 96.09  |

| SVM [21]                | 88.33   | 94.17   | 88.30  | 90.00  | 95.67  | 90.83  | 91.67  | 90.63  | 88.33  | 85.83  |
| Decision Tree [14]      | 41.67   | 50.83   | 46.11  | 51.67  | 46.67  | 49.05  | 54.17  | 53.52  | 62.67  |
| 1-D CNN [25]           | 93.75   | 94.17   | 93.89  | 93.75  | 93.50  | 94.93  | 94.61  | 95.76  | 62.67  |
| XGBoost + ASFE [49]     | 93.56   | 92.36   | 92.36  | 91.32  | 91.25  | 91.09  | 88.99  | 89.93  | 89.51  | 90.00  |
| 1-D Resnet-18*         | 95.42   | 95.63   | 96.25  | 95.99  | 95.08  | 96.63  | 96.58  | 96.12  | 95.51  | 95.90  |
| SMTNet                  | 96.88   | 96.25   | 97.08  | 96.77  | 96.46  | 97.40  | 96.07  | 96.30  | 96.25  | 95.90  |

| SVM [21]                | 80.30   | 82.48   | 79.30  | 79.27  | 83.06  | 78.99  | 79.14  | 79.52  | 79.57  | 77.91  |
| Decision Tree [14]      | 57.47   | 64.55   | 60.58  | 65.78  | 63.49  | 65.38  | 65.51  | 65.99  | 69.06  | 74.75  |
| 1-D CNN [25]           | 94.11   | 94.17   | 93.92  | 94.27  | 93.95  | 95.12  | 94.77  | 94.93  | 95.64  | 95.05  |
| XGBoost + ASFE [49]     | 93.08   | 92.39   | 92.39  | 91.38  | 91.31  | 91.19  | 89.06  | 90.00  | 89.58  | 90.07  |
| 1-D Resnet-18*         | 94.94   | 95.63   | 95.67  | 95.49  | 95.31  | 96.15  | 96.08  | 95.83  | 95.39  | 95.56  |
| SMTNet                  | 96.51   | 96.40   | 96.76  | 96.46  | 96.32  | 97.07  | 96.32  | 96.16  | 96.15  | 95.99  |
Table A5: Precision, Recall and F1-score results of different W_size of the SMTNet and comparison methods for cavitation detection in Dataset 2 (%).

| Method             | Window Size (W_{size}) | 2334720 | 1167360 | 778240 | 583680 | 466944 |
|--------------------|------------------------|---------|---------|--------|--------|--------|
| SVM [21]           | 87.88                  | 86.98   | 85.60   | 86.19  | 84.70  |
| Decision Tree [14] | 88.20                  | 82.64   | 86.21   | 86.14  | 82.42  |
| 1-D CNN [25]       | 94.64                  | 95.35   | 93.95   | 95.14  | 94.66  |
| XGBoost + ASFE [49]| 90.54                  | 90.75   | 91.53   | 91.24  | 90.37  |
| 1-D Resnet-18      | 95.85                  | 95.91   | 95.45   | 95.26  | 95.59  |
| SMTNet             | 96.45                  | 98.32   | 98.47   | 96.16  | 96.19  |

| Method             | Window Size (W_{size}) | 2334720 | 1167360 | 778240 | 583680 | 466944 |
|--------------------|------------------------|---------|---------|--------|--------|--------|
| SVM [21]           | 69.71                  | 76.66   | 68.62   | 72.00  | 70.81  |
| Decision Tree [14] | 68.27                  | 69.93   | 72.15   | 71.69  | 72.10  |
| 1-D CNN [25]       | 93.75                  | 94.93   | 93.89   | 93.75  | 93.50  |
| XGBoost + ASFE [49]| 90.56                  | 90.73   | 91.33   | 91.02  | 90.43  |
| 1-D Resnet-18      | 95.48                  | 96.63   | 96.25   | 95.99  | 95.08  |
| SMTNet             | 94.08                  | 95.40   | 95.38   | 96.77  | 96.46  |

Table A6: Precision, Recall and F1-score results of different W_{size} of the SMTNet and comparison methods for cavitation detection in Dataset 3 (%).

| Method             | Window Size (W_{size}) | 2334720 | 1167360 | 778240 | 583680 | 466944 |
|--------------------|------------------------|---------|---------|--------|--------|--------|
| SVM [21]           | 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |
| Decision Tree [14] | 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |
| 1-D CNN [25]       | 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |
| XGBoost + ASFE [49]| 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |
| 1-D Resnet-18      | 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |
| SMTNet             | 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |

| Method             | Window Size (W_{size}) | 2334720 | 1167360 | 778240 | 583680 | 466944 |
|--------------------|------------------------|---------|---------|--------|--------|--------|
| SVM [21]           | 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |
| Decision Tree [14] | 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |
| 1-D CNN [25]       | 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |
| XGBoost + ASFE [49]| 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |
| 1-D Resnet-18      | 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |
| SMTNet             | 100.00                 | 100.00  | 100.00  | 100.00 | 100.00 |
Figure A4: The effect of $W_{size}$ on cavitation detection accuracy under different methods in Dataset 1.

Figure A5: The effect of $W_{size}$ on cavitation detection accuracy under different methods in Dataset 2.

Figure A6: The effect of $W_{size}$ on cavitation detection accuracy under different methods in Dataset 3.
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Figure A7: The confusion matrix for the best cavitation detection accuracy of the SMTNet in Dataset 1.

Figure A8: The confusion matrix for the best cavitation detection accuracy of the SMTNet in Dataset 2.

Figure A9: The confusion matrix for the best cavitation detection accuracy of the SMTNet in Dataset 3.
Table A7: Accuracy, Precision, Recall and F1-score results of different frequencies of samples $FS$ of the SMTNet for cavitation detection in Dataset 1, Dataset 2 and Dataset 3 (%).

| Data   | FS      | Metrics          |
|--------|---------|------------------|
|        |         | Accuracy | Precision | Recall | F1-score |
| Dataset1 | 1562500 | 97.02     | 96.75     | 97.40   | 97.07    |
|         | 781250  | 94.43     | 94.25     | 95.12   | 94.39    |
|         | 390625  | 93.97     | 93.71     | 94.49   | 93.91    |
|         | 260416  | 93.81     | 93.52     | 94.12   | 93.73    |
|         | 195312  | 93.65     | 93.55     | 94.44   | 93.61    |
|         | 48000   | 93.39     | 93.29     | 94.18   | 93.35    |
| Dataset2 | 1562500 | 97.64     | 98.47     | 95.38   | 96.90    |
|         | 781250  | 97.14     | 98.36     | 95.29   | 96.80    |
|         | 390625  | 94.57     | 94.40     | 94.54   | 94.47    |
|         | 260416  | 94.00     | 93.78     | 94.63   | 93.95    |
|         | 195312  | 93.71     | 93.45     | 94.21   | 93.65    |
|         | 48000   | 93.57     | 93.45     | 94.33   | 93.53    |
| Dataset3 | 1562500 | 100.00    | 100.00    | 100.00  | 100.00   |
|         | 781250  | 100.00    | 100.00    | 100.00  | 100.00   |
|         | 390625  | 100.00    | 100.00    | 100.00  | 100.00   |
|         | 260416  | 99.80     | 99.61     | 99.87   | 99.74    |
|         | 195312  | 99.62     | 99.26     | 99.75   | 99.50    |
|         | 48000   | 99.28     | 98.61     | 99.52   | 99.06    |

Table A8: Accuracy, Precision, Recall and F1-score results of different frequencies of samples $FS$ of the SMTNet for cavitation intensity recognition in Dataset 1, Dataset 2 and Dataset 3 (%).

| Data   | FS      | Metrics          |
|--------|---------|------------------|
|        |         | Accuracy | Precision | Recall | F1-score |
| Dataset1 | 1562500 | 95.32     | 96.67     | 93.13   | 94.87    |
|         | 781250  | 92.79     | 93.15     | 89.76   | 91.23    |
|         | 390625  | 90.13     | 91.21     | 86.20   | 88.05    |
|         | 260416  | 88.68     | 87.00     | 88.78   | 87.81    |
|         | 195312  | 84.99     | 88.55     | 83.33   | 85.19    |
|         | 48000   | 75.88     | 77.04     | 82.14   | 75.13    |
| Dataset2 | 1562500 | 97.67     | 96.95     | 97.88   | 97.41    |
|         | 781250  | 96.77     | 96.74     | 96.73   | 96.73    |
|         | 390625  | 94.07     | 94.13     | 94.11   | 94.05    |
|         | 260416  | 90.65     | 90.94     | 90.70   | 90.63    |
|         | 195312  | 88.93     | 89.04     | 88.92   | 88.89    |
|         | 48000   | 79.34     | 79.85     | 79.37   | 79.40    |
| Dataset3 | 1562500 | 100.00    | 100.00    | 100.00  | 100.00   |
|         | 781250  | 100.00    | 100.00    | 100.00  | 100.00   |
|         | 390625  | 100.00    | 100.00    | 100.00  | 100.00   |
|         | 260416  | 99.44     | 99.45     | 99.44   | 99.44    |
|         | 195312  | 98.28     | 98.39     | 98.28   | 98.28    |
|         | 48000   | 97.44     | 97.57     | 97.44   | 97.44    |