Multi-kernel Learning based Autonomous Fault Diagnosis for Centrifugal Pumps *

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***Abstract*—Centrifugal pumps are fundamental instruments in many industry plants, whose continuously operation plays an important role in the production cycle. For improving production efficiency, autonomous pump fault diagnosis has been widely adopted by many enterprises and has also attracted great research attentions. Existing studies exploit machine learning algorithms for autonomous pump fault diagnosis, which generally needs human knowledge to select distinctive data features. To avoid the bias of human selection, this paper proposes a multi-kernel learning (MKL) based autonomous pump fault diagnosis method. It trains basic classifiers (BCs) by each feature and weightly combines the basic classifiers to form the combined classifier for fault diagnosis. An autonomous BC weighting algorithm is proposed, which trains the combination weights of the BCs autonomously. We show the MKL based fault diagnosis method provide more accurate fault detection than the existing methods and without the need of human experts' interventions.**

***Index Terms*—Multi-kernel learning, Centrifugal Pump, Autonomous, Fault Diagnosis**

I. Introduction

Centrifugal pumps play a vital role in many industry plants. The continuous availability of such mechanical components are absolutely essential in the production cycle. For example, in steel-melting plant, many centrifugal pumps are used, which are responsible for pumping water to cool the steel-melting machines or discharging the waste water. They are critical supporting system for the production system.

However, because of the high speed rotation of the impellers in the centrifugal pumps, the pumps prone to encounter different kinds of runtime faults, such as *faulty bearing, defection on the impeller and cavitation etc*. Quickly detecting and diagnosing of these faults are critically important for shortening the reparation time to guarantee the safety and efficiency of the production system.

To achieve above goal of run-time pump fault diagnosis, the production companies generally adopt three policies in using the pumps. 1) using redundant pumps, so that backups can be started as soon as some pumps are faulty; 2) install various sensors on the pumps for status monitoring, fault detection, and preventive maintenance. 3) investigating various fault diagnosing methods for quickly fault diagnosing and targeted reparation.

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A. Related works

For its importance, pump fault diagnosis problem has been widely investigated and different systems and methods have been proposed. According to the sensors used in the pump fault diagnosis systems, existing work can be roughly categorized into three categories.

1) **Vibration sensor based**. A large category of fault diagnosing system is using high frequency vibration sensors [4] [10] [20] [1] [12] [17]. By installing one or more vibration sensors on the pumps, the states of the pumps can be online identified by either signal processing and machine learning algorithms. .
2) **Pump model based**. [15] [13] [5] A limitation of using vibration sensors is that the vibration sensors are expensive. Other approaches investigated to use pump model and other kinds of sensors such as pressure, flow and temperature for fault diagnosing. Machine learning based approaches are widely used in this kind of approaches.
3) **Sensor Fusion based**. Sensor fusion is one important way to improve the fault identification accuracy. Ao et al. studied robustness of sensor fusion for outlier detection [2]. Bayesian networks, fuzzy model and neutral networks are widely adopted in sensor fusion-based pump fault diagnosis systems. [7] [9].

Whatever the sensors or the fault detection methods are used, a crucial step is to discover some distinctive sensor data features and associate them to some specific faulty state [18] [11]. So that the specific faulty state can be inferred when the associated data features are observed, which is the feature extraction and diagnosis model training phase.

In existing work, this process is heavily dependent on the human knowledge in extracting the sensor features and building the identification model. The sensor features are extracted using different methods, such as by moving window statistics [7], frequency domain transformations [6], or wavelet domain transformations [11]. Then with the help of labelled data set, these features' capacity of discernment are evaluated [19]. The more discerning features will be selected in building the classification model for pump fault diagnosis. But such manually feature extraction methods have following limitations:

1) Because different pump systems may have different fault features, the manually model building process limits the wide application of a trained system on the other systems because the faulty features maybe different due to the different environments.
2) Even human experts can hardly identify distinguish features in complex cases when there are many faults and some faults have similar features. The bias in feature extraction and model building will lead to fault diagnosis error.

B. Main Contribution

In [8], Lei et al. proposed an on-line model updating method based on multi-kernel learning for health care applications. In this paper, we propose a multi-kernel learning based autonomous pump fault diagnosis method, which overcomes the limitation of manually feature extraction and manually model training. Multi-kernel learning is a widely adopted method for adaptively feature extraction building [3] [16] [14] in machine learning studies. It trains a set of basic classifiers (BCs) by each single feature of data, which are called kernel classifiers. The BCs are then linearly combined to form a Combined Classifier (CC). The linear weights of the BCs in the CC are learned from the training data. So that the BCs and the weights of BCs in CC are both learned automatically from the training data. This enables adaptive feature extraction and multi-kernel model building purely from the training data without the needs of expert knowledge.

We design a MKL-based autonomous pump fault diagnosis system. We show it has better classification accuracy than the state of the arts.

II. Problem Model

A. Problem Discription

The problem of diagnosing pump faults from run-time sensor data is considered. We suppose the pump has n states, among them, the first state is healthy and the other $n-1$ states represent $n-1$ different faults. The sensory data of the pump is on-line collected with some specific frequency. By statistically analysis and signal processing, at each time interval t, we consider totally m basic features can be extracted from the sensory data, such as the variance of vibration, mean of pressure, variance of pressure etc. These basic features are denoted as $\mathbf{x}^t = \{x_1^t, x_2^t, \cdots, x_m^t\}$. The pump state at time t is denoted by $\mathbf{y}^t \in [1, 2, \cdots, n]$.

Definition 1 (Autonomous Pump Fault Diagnosing). *Given $\boldsymbol{x}^1$ to $\boldsymbol{x}^t$ and the set of faults $\mathbf{F} = \{1, 2, \cdots, n\}$, the problem is to identify the most possible state of $\boldsymbol{y}^t$ at time t.*

$$\arg\max_{i \in \mathbf{F}} p\left(\mathbf{y}^t = i | \mathbf{x}^1, \mathbf{x}^2, \cdots \mathbf{x}^t\right) \tag{1}$$

If Markov state is assumed, the pump state will be identified by the sensor data at time t. So the problem can be simplified as: $\arg\max_{i \in \mathbf{F}} p\left(\mathbf{y}^t = i | \mathbf{x^t}\right)$.

B. Multi-kernel Learning Model

This paper proposes a multiple kernel learning (MKL) model for pump fault diagnosis. The proposed learning model is as following in Eqn.(2).

$$G(\mathbf{x}) = \text{sign}\left[\sum_{j=1}^{m} a_j G_j(\mathbf{x}_j)\right] \tag{2}$$

In (2), we omit the time index to consider only the instance at time t. $[m]$ is used to denote $\{1, 2 \ldots, m\}$. $\mathbf{x}$ is the user feature data set; $\mathbf{x}_j$ is a subset of $\mathbf{x}$, i.e., $\mathbf{x}$ is divided into m subsets of features. $\{G_j : G_j(\mathbf{x}_j) \in \{-1, 1\}, j \in [m]\}$ is an off-line trained basic classifier (BC), which predicts the user state based on the feature subset $\mathbf{x}_j$; $a_j \in [0, 1]$ is the learned weight for combining the basic classifier $G_j(\mathbf{x}_j)$. There are m BCs and the weights are assumed normalized, i.e., $\forall j \in [m], a_j \geq 0$ and $\sum_{j=1}^{m} a_j = 1$. The output $G(\mathbf{x})$ is a binary classifier, which outputs either 1 or -1 to predict the user state.

Note that, for presenting clarity, we consider the combined classifier $G(\mathbf{x})$ a binary classifier, which outputs either -1 or 1. The multiple state classifier can be composed from binary classifiers as stated in Section III.

III. MKL based Pump Fault Diagnosis

We present the MKL based pump fault diagnosis system and algorithms in this section.

A. Overview

The block diagram of multi-kernel learning based pump fault diagnosis system is given as following:

It contains mainly three blocks:

1) Sensor data collection module. By this module, data is collected from sensors equipped on the central pumps.

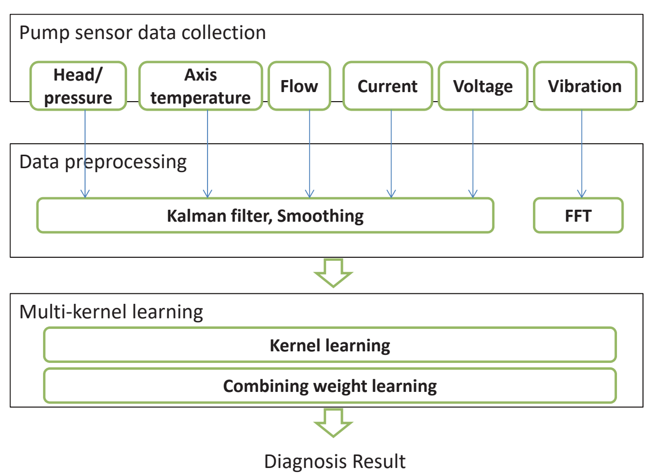

Fig. 1. The block diagram of multi-kernel learning based pump fault diagnosis system

Each pump is monitored by following sensors: 1) head sensor, which monitors the pressure difference of the inlet and outlet of the pump; 2) Axis temperature sensor, which monitors the temperature of the axis; 3) Flow sensor which monitors the flow volume per second of the pump; 4) Current; 5) Voltage sensors which monitors the power used by the pump; 6) Vibration sensor, which returns the 3-axis acceleration of the pumps in 1000Hz frequency.

2) Data processing module. The sensor data is collected continuously into a Kafka database, but the sensor data is noisy. Data processing model is responsible to exclude the data outliers and smooth the data via Kalman Filter.
3) Multi-kernel learning module: the multi-kernel learning model includes an off-line phase and an on-line phase. In off-line phase, the basic classifiers (called kernels) are trained and the weights for combining the basic classifiers are trained. In on-line phase, the MKL module output online diagnosis results of the monitored pump.

B. Multi-Kernel Learning (MKL) Module

Training of multi-kernel learning model includes 1) training of basic classifiers and 2) training of combining weights.

1) Training of basic classifiers: In training of basic classifiers, each sequence of sensor data is processed to extract a set of feature sequences. For example, for the 'head' sensor data sequence, the head sequence will be processed by a slicing window of length l to extract the feature sequences *mean sequence*, *variance sequence*, *min sequence*, *max sequence* etc. of the sensor data. These feature sequences are denoted by $\mathbf{x}_i$. From n sensors, if k feature sequences are extracted from each sensor sequence, nk feature sequences will be extracted. We consider each sequence has length T. So nk feature sequences of length T will be built.

We then train basic classifier based on each feature sequence and their corresponding label sequence of pump states. A basic classifier $\hat{\mathbf{y}}_i = \mathbf{f}_i(\mathbf{x}_i)$ is trained using the training data $\{y_{[1:T]}, x_{i,[1:T]}\}$, where $\mathbf{x}_i = x_{i,[1:T]}$ is the ith feature sequence data and the training label $y_{[1:T]}$ is the corresponding pump state sequence. Totally nk basic classifiers will be trained: $\hat{\mathbf{y}}_i = \mathbf{f}_i(\mathbf{x}_i)$, $i \in \{1, 2, \cdots, nk\}$. The flowchart of basic classifier training is shown in Fig.2. In practice, each basic classifier is trained by a SVM model.

2) Training of combining weights: After training of the basic classifiers, we get nk basic classifiers. These classifiers are linearly combined to generate combined classifier. The initial weights are uniformly assigned as $w_j = \frac{1}{nk}, j = \{1, \cdots, nk\}$.

$$\hat{\mathbf{y}}(\mathbf{x}) = \text{sign}\left[\sum_{j=1}^{nk} w_j \mathbf{f}_i(\mathbf{x}_i)\right] \quad (3)$$

The combining weights are then trained based on the training data. The policy is to adjust the combining weight w_i based on the consistence of y_t (label of tth sample) and the output of $\mathbf{f}_i(\mathbf{x}_{i,t})$. If the label y_t is inconsistent with $\mathbf{f}_i(\mathbf{x}_{i,t})$, w_i will be decreased by $w_i\beta$, where $0 < \beta < 1$.

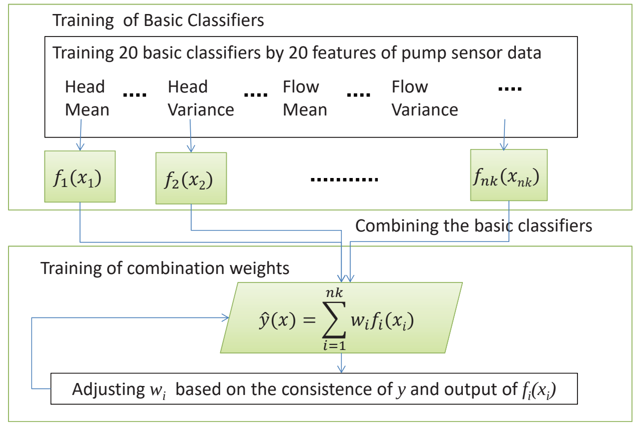

Fig. 2. Flow chart of MKL model training including the basic classifier training and the combining model training

Then the weight vector will be normalized for keeping their summation be 1. The process repeats until the convergence of $\{w_i\}$ or finishing by the training data. The process to train the combining weights is shown in Fig.3. The parameter β can be chosen by controlling the discounting speed of the weights. The smaller the beta, the higher the discounting speed.

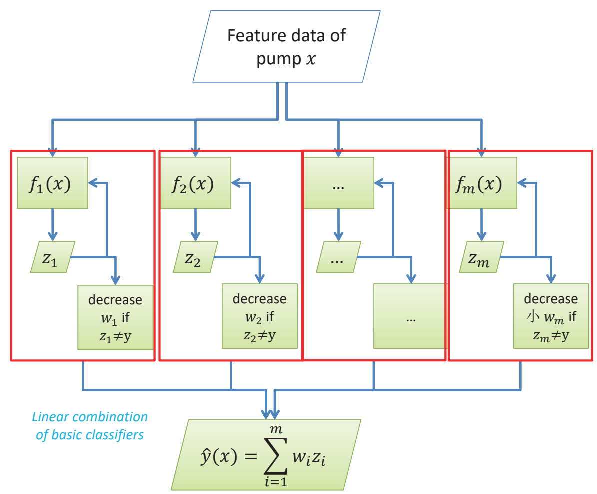

Fig. 3. The block diagram of training the weights of basic classifiers.

C. Online Model Test in MKL

An important advantage of MKL-based learning is that the trained model can be on-line tested to check whether the model has outdated if the pump conditions or environments change. This can be checked by the margin the combined classifier.

Definition 2 (Classification Margin)**.** *The margin of the combined classifier is defined as the distance from $\hat{\mathbf{y}}(\mathbf{x})$ to $\sum_{j=1}^{nk} w_j \mathbf{f}_i(\mathbf{x}_i)$, i.e.:*

$$M(G(\mathbf{x})) = \left|\hat{\mathbf{y}}(\mathbf{x}) - \sum_{j=1}^{nk} w_j \mathbf{f}_i(\mathbf{x}_i)\right| \quad (4)$$

Since $\hat{\mathbf{y}}(\mathbf{x})$ is the sign of $\sum_{j=1}^{nk} w_j \mathbf{f}_i(\mathbf{x}_i)$, the classification margin indicates the distance from the sign to the weighted sum of the BCs' classification results. For example, when $\hat{\mathbf{y}}(\mathbf{x}) = 1$ and $\sum_{j=1}^{nk} w_j \mathbf{f}_i(\mathbf{x}_i) = 0.7$, the margin is 0.3. When $\sum_{j=1}^{nk} w_j \mathbf{f}_i(\mathbf{x}_i) = 0.8$, the margin is 0.2. So $0 < M(G(\mathbf{x})) < 1$, the smaller the margin, the more confident the output classification label is. Based on the results of the classification margin, we can test the confidence of the off-line trained combined classifier on distinguishing different kinds of faults. When the average margin becomes larger, it means it becomes easier to generate classification errors when some noises are presenting. So when the learning margins of predicting several faults are rather large, the model need to be retrained.

D. Implementation of MKL

1) Basic Classifier Implementation: MKL provides a framework for adaptive feature selection for pump fault diagnosis. The basic classifiers (BCs) in MKL can be implemented in different ways. In this paper, we implement the BCs by Supporting Vector Machines (SVM). Each BC is trained by each feature sequence and the corresponding fault state label sequence. So $\hat{\mathbf{y}}_i = \mathbf{f}_i(\mathbf{x}_i)$, $i \in \{1, 2, \cdots, nk\}$ are trained as SVM classifiers.

2) Combined Classifer Implementation: The combined classifier is chosen as a linear combination of the SVM basic classifiers. Initially, all the weights are equally assigned and the weights are updated when each weight training sample is used.

3) Sensor data collection from pump system: We also have installed pump station state monitoring system in three pump stations in Baotou iron and steel plant company. Totally more than 20 pumps are monitors by variation sensors, temperature sensors, presser sensors, voltage and current sensors etc. The interface for pump state monitoring system is shown in Fig.4. But for the lack of labeled fault events in the real systems, we conduct experiments using online dataset. The proposed algorithms can adapt when enough labeled fault data can be collected in the real systems.

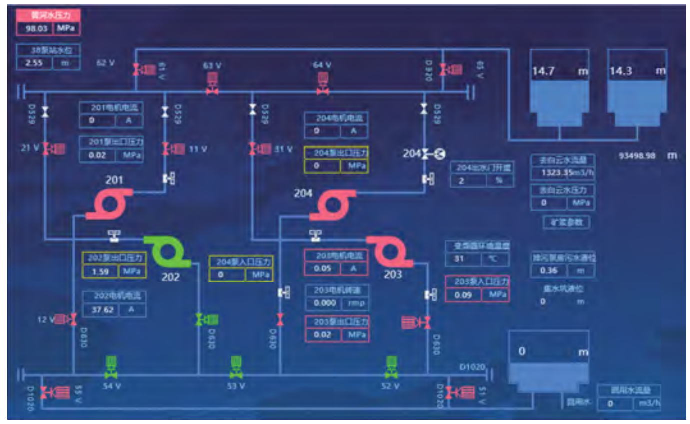

Fig. 4. Interface of pump state monitoring system deployed in Baotou Iron and steel company

IV. Experiment Results

A. Experiment Settings

We carry out experiments to test the performances of the proposed MKL-based pump fault diagnosis method. We use the same dataset as used in the predictive maintenance toolbox in Matlab 2018. The experiments are carried out in Matlab2018.

The dataset contains 500 samples. Each sample is composed by twenty kinds of data features and corresponding state label of the pump. The twenty features are: $\{'Mean1'\}\{'Mean2'\}\{'Mean3'\}\{'Mean4'\}$ $\{'Max1'\}\{'Max2'\}\{'Max3'\}\{'Max4'\}\{'Kurtosis1'\}$ $\{'Kurtosis2'\}\{'Kurtosis3'\}\{'Kurtosis4'\}\{'Variance1'\}$ $\{'Variance2'\}\{'Variance3'\}\{'Variance4'\}\{'OneNorm1'\}$ $\{'OneNorm2'\}\{'OneNorm3'\}\{'OneNorm4'\}$. The pump has ten states, which are: *'Healthy', 'ClearanceGapWear', 'ImpellerOutletDeposit', 'ImpellerInletDeposit', 'AbrasiveWear', 'BrokenBlade', 'Cavitation', 'SpeedSensorBias', 'FlowmeterBias', 'PressureSensorBias'* respectively.

The dataset is separated into tree parts. The first part contain n_1 samples, which is used to train the SVM basic classifiers. The second part contains n_2 samples, which is used to train the combining weights of the BCs. The third part contains n_3 samples, which are used to test the fault diagnosis performance of the proposed method.

B. Training of the BCs

We select any two neighbouring features to train a SVM basic classifier, so that 10 basic SVM classifiers are trained by n_1 training samples. We vary n_1 from 50 to 200 to test how the accuracy of the BCs will be impact by the number of number of training samples.

We visually plot the characters of nine groups of selected features in distinguishing the pump's healthy state from faulty state. The results are shown in Fig.5. From the figure, we can see the 7th and 9th feature groups have better differential ability than other features to distinguish the pump's state from *'Healthy'* to *'Faulty'*.

By setting $n_1 = 110$, ten basic SVM classifiers are trained. The average classification accuracies of these BCs are then tested by the n_3 testing samples. The average classification accuracies of these 10 BCs are plotted in Fig.6.

From the figure, we can see that the 7th and 9th BCs have better classification accuracy than other BCs. This coincides the observation that the the 7th and 9th groups of features have better differential ability than other features. But our goal is not the select these features manually, but to design a multi-kernel classifier which can select the features adaptively.

C. Training of the Combining Weights

After training the basic classifiers, we train the combining weights using the n_2 training samples. Initially, the weights are equally assigned to each BC, i.e., $w(i) = \frac{1}{10}$ for the 10 BCs.

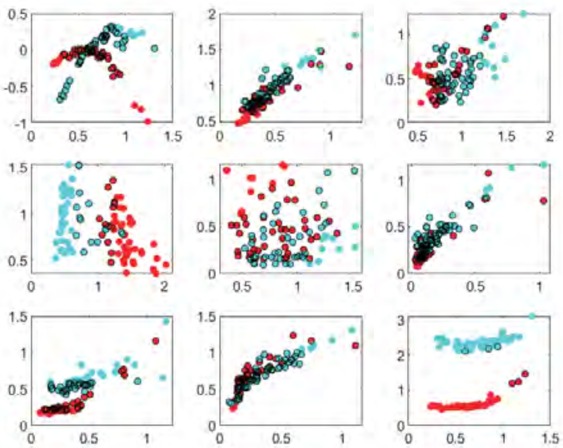

Fig. 5. A visual illustration of different features' differential ability from the pump's healthy state from other faulty states.

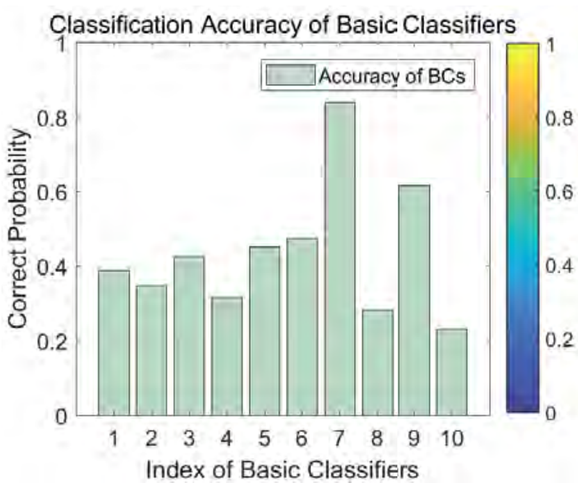

Fig. 6. Classification accuracy of 10 BCs when $n_1 = 120$

Then the weight updating scheme shown in Fig.3 is applied to update the weights for BCs using the weight training samples.

For different combinations of n_1 and n_2, the resulting accuracies of the BCs and the trained combining weights are plotted in Fig.7 to Fig.9. In Fig.7 when $n_1 = 110$, the 7th and 9th BCs have better classification accuracy. By using $n_2 = 100$ weight training samples, the combining weights are learned. It can be seen that the 7th BC has the highest weight, which is coincide with our expectation. In Fig.8, when n_1 is increased to 130, the classification accuracies of the BCs increase. The learned combining weights are also plotted. In Fig.9, when n_1 is increased to 150, the accuracies of several BCs have been increased to nearly 1. We also increase n_2 to 150, and we can see the trained combining weights are highly correlated to the classification accuracies of the BCs. This shows the weight training can automatically select the BCs with better classification accuracy, which provide adaptive feature selection capability.

D. Improvement of the Classification Accuracy

The updating of combining weights will improve the classification accuracy of the combined classifier. We select the parameter β in the range $\{0.6, 0.7, 0.8, 0.9\}$. Fig.10 shows how does the accuracy of combined classifier improve as the combining weights are updated by the weight training samples. We can see when $\beta = 0.6$, the combining weights are updated very quickly to reach a good classification accuracy. When $\beta = 0.9$, the optimization process of the combination weights becomes much slower. The result indicates that, we can obtain a quick weight updating by setting smaller β.

E. Improvement of the Classification Margin

At last we evaluate how the updating of the combining weights will update the classification margin of the combined classifiers.

As defined in Definition 2, the smaller the classification margin is, the better the robustness of the combined classifier has. Fig.11 shows the margins of the combined classifier before and after weight updating. The horizontal axis shows the number of samples used to train the weights. The blue line shows the margins of the combined classifier after weight training. It can be seen that the margin after weight training is much smaller than the classification margin before weight training. So that, the combined classifier has much more robust classification capability than that before weight updating.

V. Conclusion

In this paper, we propose a multi-kernel learning based pump fault diagnosis method. It trains basic classifiers by evenly dividing the feature sets and then train the combining weights of the basic classifiers to generate a more powerful combined classifier. We show this multi-kernel learning method can select vital features automatically, which avoid the requirement of expert knowledge in feature selection and weighting. The weights of the combined classifier can be updated quickly and the combined classifier has much better classification margin than that before weight updating. The proposed method is expected to have important impact in smart pump diagnosis via sensing data, since most of computer scientist are not familiar with pump characteristics. We will work on the implementation of MKL method in practical pump stations in our future work.

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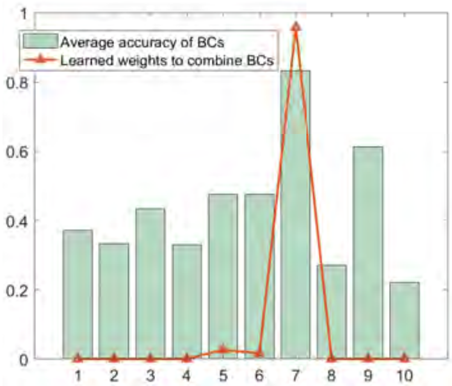

Fig. 7. Combining weights and BC accuracies when $n_1 = 110$, $n_2 = 100$

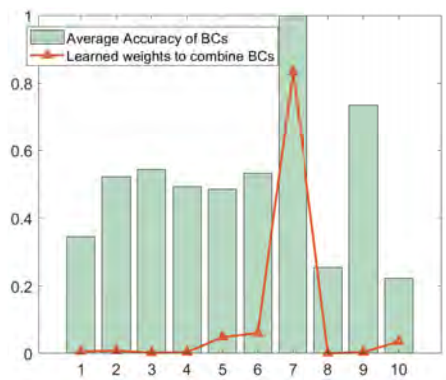

Fig. 8. Combining weights and BC accuracies when $n_1 = 130$, $n_2 = 100$

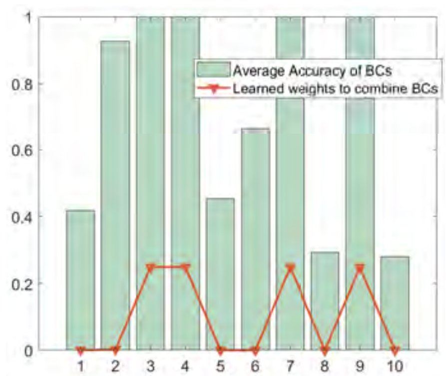

Fig. 9. Combining weights and BC accuracies when $n_1 = 150$, $n_2 = 150$

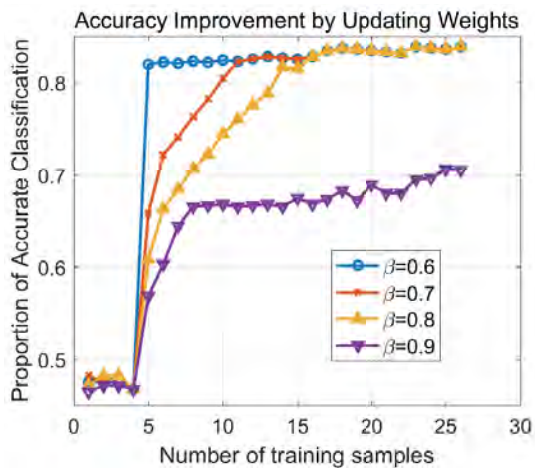

Fig. 10. Flow chart of MKL model training including the basic classifier training and the combining model training

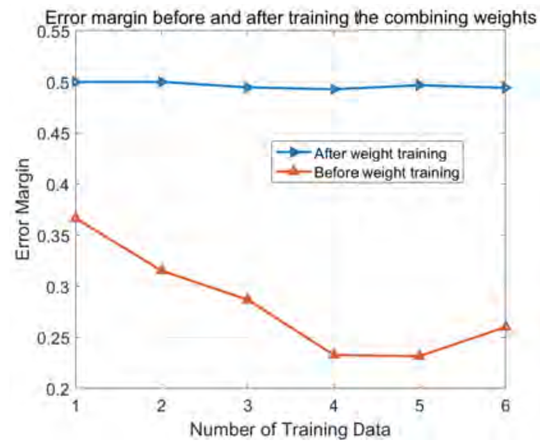

Fig. 11. Flow chart of MKL model training including the basic classifier training and the combining model training

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