Retargeting PHM tools: from industrial to medical field

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Abstract

Prognostics and Health Management (PHM) approach, and theoretical models have had great success for industrial systems. Therefore, this accomplishment motivates us to think about potential extension of the PHM approach in such area as the medicine. The aim of this paper is to apply an adaptation of a PHM model from fault diagnosis of aircraft engine to diagnosis human heart disease. For that adaptation, an algorithm for retargeting extreme learning machine (ID-RELM) is applied. The complete process from data pre-processing to classification is developed. Numerical results using heart disease benchmark dataset showed that the combination of random forest and ID-RELM provides the highest classification accuracy and outperforms other algorithms in classifying this chronic disease status.

1. Introduction

Many researchers from various engineering fields have been focused on Prognostics and Health Management (PHM) tools in order to decrease the maintenance cost of industrial resources and enhance system safety, availability, and reliability. PHM implementation steps involve: data acquisition, data preprocessing, detection, diagnosis, prognosis, decision making, and human-machine interface (Atamuradov, Medjaher, Dersin, Lamoureux, & Zerhouni, 2017). Works piloted in PHM research have concentrated on developing accurate and robust models to evaluate the systems health state by making diagnosis, prognostic, and support decision making.

Automatic diagnosis and prognosis in medical domain have been active areas in computer science field in the last decades. Various medical domains such as oncology and chronic diseases attract researches. In this work, we are interesting in cardiology field. Recall that heart disease is the major cause of death in the world and the number of patients with heart disease is growing each year (Ramalingam, Dandapath, & Raja, 2018). According to World Health Organization (WHO) reported data, around 17.3 million persons died worldwide from cardiovascular diseases (CVDs). This statistics shows the need of having computer aided diagnosis (CAD) system that is able to provide a preliminary assessment of a patient based on simple accessible medical tests (Atallah & Al-Mousa, 2019). CAD for heart disease was widely developed using data mining and machine learning (Kolukısa et al., 2019). However, the performance still needs improvement to make accurate classification.

The aim of this paper is to apply an adaptation of a PHM model from fault diagnosis of aircraft engine (Zhao, Song, Pan, & Li, 2017) to human heart disease diagnosis. This PHM model is based on a new strategy by retargeting extreme learning machine (ELM) algorithms. ELM is a single feedforward neural network. Its structure involves a single layer of hidden nodes, where the weights between inputs and hidden nodes assigned randomly, and remain constant during training and testing phases. On the other hand, the weights that connect hidden nodes to outputs can be trained very fast. The idea behind retargeting ELM is to avoid limits of the original one regarding the random hidden nodes generation by retargeting its label vectors. The proposed method need less hidden nodes to achieve the same classification performance, which improves the processing real time.

In order to develop a CAD for heart disease, a new scheme is proposed based on PHM adaptation using UCI heart disease dataset (*Cleveland Heart Disease Dataset*, 1990). The proposed scheme consists of: (a) the pre-processing step to improve data quality (missing data imputation and scaling dataset), (b) the feature selection step to improve classification performance (based on embedded method), (c) the diagnosis phase to identify the absence or the presence of heart disease (using Improved Dragging Regularized ELM (ID-RLM)). The performance of our proposed scheme is compared with previous work.

The organization of the rest of this paper is as follows. Section 2 highlights the similarities and differences between medical and engineering PHM. Section 3 describes the adapted approach involving pre-processing phase, feature selection, classification and evaluation metrics. In Section 4, experimental results to demonstrate effectiveness of our system are provided. Finally, a conclusion and future works are presented in Section 5.

2. ENGINEERING PHM VS MEDICAL PHM

PHM discipline was originally developed in engineering field. Many works in PHM research focused on designing reliable and robust models for assessing components health states for different applications, in order to support decision making (Gouriveau, Medjaher, & Zerhouni, 2016; Chebel-Morello, Nicod, & Varnier, 2017). This success of PHM in industry motivates us to think about the implementation of this process in the medical field. In the last decades, computer-aided diagnosis and computer-aided prognostics in medical domain have been active areas in computer science field. However, the accuracy and reliability are still lacking. The main duties of PHM expertise are to identify incipient system fault or component; to implement failure diagnostics and prognostics, and health management (Atamuradov et al., 2017). All of those objectives are needed in the medical filed as well. In other words, we look for detecting body or organ fault (disease), to perform disease diagnosis and prognostics, and health management. Table 1 shows the similarities and differences between machine and human body in PHM view. We may infer that an adaptation of PHM can be applied in the medical filed with two key points being taken into account: 1) Working on human body is more complicated, this is due to the complexity of organs and the interactions between them are sometimes unknown and less predictable. Furthermore, any mistake leads to critical consequences. 2) The data generation and sharing in medical filed still hard to achieve, and the privacy of patients should be taking in consideration.

3. ADAPTED PHM TOOL

We here present the adaptation process of the proposed PHM tool for aircraft engine (Zhao et al., 2017) to heart disease diagnosis. Figure 1 shows the general schematic diagram of our proposed tool adapted from (Zhao et al., 2017) to diagnose heart disease. The details of each processing stage are described in the subsequent sections.

3.1. Data description

The Cleveland dataset (*Cleveland Heart Disease Dataset*, 1990) used in this study was created by the University of California Irvine (UCI) Machine Learning Repository heart disease dataset, including four independent databases funded by four independent medical institutions. The Cleveland dataset contains 303 cases of patient data involving some missing values. Table 2 shows the Cleveland dataset attributes with their definitions and types.

3.2. Data preprocessing

In order to achieve more accurate results, data pre-processing is an important step in changing raw heart disease dataset into a clean and understandable format for analysis. The following sub-sections discuss the techniques that have been applied to improve the quality of our dataset.

3.2.1. Missing data

In health analytics, missing data may be obvious due to many reasons: damaged equipment, misplaced or imprecised measurements, and some technical faults by physicians or nurses. In computer science, the most serious problems of missing values are slowing down the analytic processing due to lower efficiencies, and the possibility of compromising information extracted from the data leading to faulty decisions. In literature, to deal with missing data, three strategies may be implemented. (1) Missing data ignoring techniques: the simplest one, by deleting the cases that contain the missing data (Houari, Bounceur, Kechadi, Tari, & Euler, 2016). Deleting any information is not recommended in our case where the size of the data is small. (2) Missing data modeling techniques: The idea here is to develop a model from the existing data and to generate suggestions based on the distribution of the data (Houari et al., 2016). (3) Missing data imputation techniques: These techniques complete the missing data in the dataset with a potential value (Cleophas & Zwinderman, 2016) such as regression, K-nearest neighbors (KNN), and multiple imputations tools. In this paper, we are going to apply the KNN techniques, which is an algorithm that is useful for matching a point with its closest k neighbors in a multidimensional space (Malarvizhi & Thanamani, 2012). It can be used for data that are ordinal, continuous, categorical, and discrete which makes it particularly useful for dealing with all types of missing values.

3.2.2. Scaling data

In this step, data columns are re-scaled to a range of $[0 - 1]$ for two causes. The first is one is to simplify the complexity of digital computing. The second one is to get rid of attributes in the largest numeric range while controlling attributes in the smallest numeric range (Sahu, Mohanty, & Rout, 2019).

3.2.3. Feature selection

Feature selection process is very significant to find most relevant attributes to the classification and then to the diagnosis.

Table 1. Industrial system vs. human body contrast in PHM view.
Acronyms: MRI: Magnetic Resonance Imaging; CT: computerized tomography; WSI: whole slide imaging; RUL: remaining useful life.

	Industrial system	Human body
Complexity	Interactions between components and failure modes may be well-defined	More complicated interactions. Biological failure modes of a human body or organs could be less predictable
Risk factors	Component aging, damage accumulation and fault progression	Concepts on natural history, clinical course, diseases progression, lifestyle, and environment
Data generation	Sensors data is the most type used in industry (Vibration, temperature, humidity, etc.)	Various types of data: wearable sensors (Blood pressure, heart rate, Fasting blood sugar, etc.), images (MRI,CT, ultrasounds, WSI, etc.), reports and prescriptions text, clinico-histological features, etc.
Diagnosis	Estimation of the health state of a system based on observations (sensors) and analysis (models and algorithms)	Disease detection by identifying the type, and the cause based on clinico-histological data, etc.
Prognostics	Predict the component RUL	Predict getting the disease based on risk factors Predict the recurrence of disease
Decision-making	Determine optimal maintenance policies	Select optimal treatment, and prevention policies

Table 2. UCI heart disease dataset description.

	Feature	Input type	Input range
age	Age in years	Numeric	$[29, 77]$
sex	Sex	Binary	0 = female 1 = male
cp	Chest pain type	Nominal	1 = typical angina 2 = atypical angina 3 = non-anginal pain 4 = asymptomatic
trestbps	Resting blood pressure on admission to the hospital in mm Hg	Numeric	$[94, 200]$
chol	Serum cholestoral in mg/d	Numeric	$[126, 564]$
fbs	Fasting blood sugar is greater than 120 mg/dl or not	Binary	0 = false 1 = true
restecg	Resting electrocardiographic results	Nominal	0 = normal 1 = having ST-T wave abnormality 2 = left ventricular hypertrophy
thalach	Maximum heart rate achieved	Numeric	$[71, 202]$
exang	Exercise induced angina	Binary	0= no 1=yes
oldpeak	ST depression induced by exercise relative to rest	Numeric	[0,6.2]
slope	The slope of the peak exercise ST segment	Nominal	1 = upsloping 2 = flat 3 = downsloping
ca	Number of major vessels (0-3) colored by flourosopy	Nominal	0-3
thal	The heart status	Nominal	3 = normal 6 = fixed defect 7 = reversable defect
num	Diagnosis of heart disease		0 = less then 50% diameter narrowing (normal) 1 = greater then 50% diameter narrowing (patient)

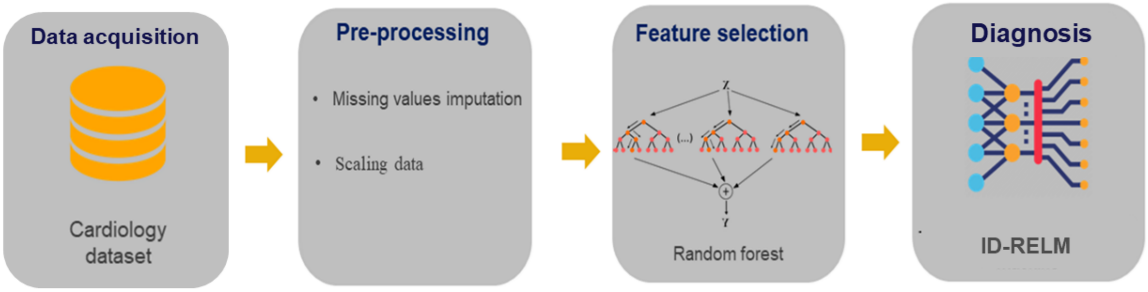

Figure 1. A general scheme of our CAD of heart disease.

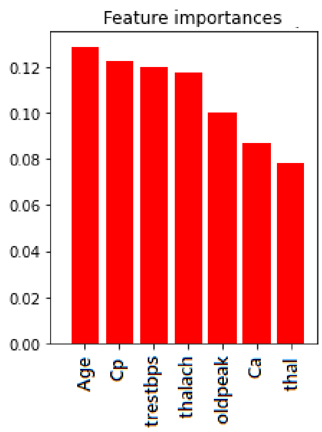

Figure 2. Features selected by RF algorithm on UCI dataset and their score.

It has many advantages: (1) To make the model simpler to interpret. (2) To decrease the variance of the model, and therefore over-fitting. (3) To decrease the computational time and cost. (4) And finally, the most important one, is to increase the performance of the model (Turgut, Dağtekin, & Ensari, 2018). In the literature, there are three main types of feature selection techniques: filter, wrapper, and embedded methods. In this paper we will choose the third one, which combine the advantages of filter and wrapper methods as implemented by algorithms that have their own built-in feature selection methods. Random Forests (RF) are often used as embedded feature selection. The reason is that tree-based strategies used by RF can logically rank by how well they will improve the clarity of the node (Pan & Shen, 2009). Starting from the top of the trees, we first find nodes with the highest decrease in impurity, while nodes with the minimum decrease in impurity occur at the end of trees. Thus, by pruning trees below a particular node, we can create a subset of the most important features. Figure 2 shows the features selected by RF with their score, where x-axis is the feature indexes and y axis is the feature importance.

3.3. Diagnosis

Extreme learning machine (ELM) is proposed and implemented by (Liang, Huang, Saratchandran, & Sundararajan, 2006) as a single hidden layer feedforward network. It was widely used in many machine learning tasks such as classification, regression, etc. The reason behind this success is the efficiency and the effectiveness of the model based on two main advantages: (1) ELM generates randomly hidden layer biases and input weights. Unlike the traditional neural network, ELM determines the output weights without tuning by iterations as error back-propagation. (2) ELM searches to minimize both training errors and the norm of output weights, based on Bartlett's theory which benefits the generalization on the unseen data. Despite the evidence of the drawback of ELM, it has a weak point presented in the generation of extra hidden nodes to reach the same generalization performance as the traditional neural networks. A large size network leads to more computational time in the testing phase, which is not suitable for testing time view. Therefore, a lot of proposed algorithms lean to compact the ELM architecture. The traditional methods overcome this disadvantage by optimizing the network structure. However, a data structure viewpoint is proposed by (Zhao et al., 2017), which is different from the previous viewpoint of network structure. They care about the margin instead of the reference points, so a flexible dragging strategy is developed. We here apply the improved version (ID-RELM) for diagnosis, which abandons the reference points and can improve the classification performance by retargeting the ELM label vector. In this way, one can obtain a higher classification performance with a lesser network size and processing time. This seems to be beneficial for a real time application for heart disease diagnosis.

3.4. Performance Metrics

The used model is evaluated using the below metrics. Let TP be the true positive means number of patient who don't have heart disease (Healthy) which are predicted correctly; TN the true negative means number of patient with heart disease (Unhealthy) which are predicted correctly; FP the false positive means number of normal which are predicted as patient and

FN the false negative means number of patient which are predicted as normal.

- Accuracy refers to the whole number of instances that may be classified correctly. It is given by (Tsai & Yu, 2015).

$$\text{Accuracy} = \frac{TP + TN}{TN + TP + FP + FN} \tag{1}$$

- Sensitivity measures the quantity of TP instances, which are correctly identified by the classifier. It is given by

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{2}$$

- Specificity measures the quantity of TN instances, which are correctly identified by the classifier. It is given by

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{3}$$

- Precision measures the amount of predicted TP that is truly related to the TP class. It is given by

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

- F1-measure is a combination of precision and sensitivity. Therefore, a high value of F-measure shows a high value of both precision and sensitivity (Majid, Ali, Iqbal, & Kausar, 2014). It is given by

$$\text{F1-measure} = 2\frac{\text{Precision} * Sensitivity}{\text{Precision} + Sensitivity} \tag{5}$$

- The Receiver Operating Characteristics (ROC) curve is a graphical plot used to compare the performance of a binary classifier, which in our case would be normal or patient. Area Under Curve (AUC)
- AUC is calculated for assessing performance of the classifier and provides an examination of the classifier stability and consistency.

4. EXPERIMENTATION

This experiment is compiled and ran in google colab environment with python language using scikit-learn bibliography. The default values of functions are used for all parameter values that are not explicitly stated. Before experiments, we firstly prepared our dataset through the imputation of missing values using KNN technique. We have implemented KNN with $K = 4$. Secondly, a re-scaling method have been applied to re-scale continuous features into the range $[-1, 1]$. Then, we have splitted randomly UCI heart disease dataset into training set 70% and the testing set 30%. For the diagnosis step, we started by applying traditional ELM architecture to compare its performance with ID-RELM algorithm. We then applied RF for feature selection. Table 3 shows the performance of the three methods on UCI heart disease dataset without retargeted technique (ELM), with retargeted technique (ID-RELM), and RF based feature selection combined to ID-RELM (ID-RELM & RF). The application of the simple ELM classifier gives a modest results with 0.81 accuracy, 0.89 sensitivity of healthy patient and 0.74 sensitivity of unhealthy patient. It also generates too much hidden nodes for this performance (153 hidden nodes), which are not as good as for the real time processing. We can observe that the classifier performance has been improved after using ID-RELM. We notice a higher accuracy 0.88, sensitivity and specificity. This is obtained for only 42 hidden nodes (see Table 3). ID-RELM method seems to be a good technique to classify UCI heart disease dataset with lower testing processing time. Figure 3 shows the same results using ROC curve. the figure compares the AUC of simple ELM, ID-RELM, and ID-RELM RF. We can notice an improvement when ID-RELM technique is applied (from AUC = 0.81 to AUC = 0.87). By combining RF features selection with ID-RELM, the highest classification performances are achieved as we can remark in Table 3 (the accuracy increases to 0.94 and AUC is 0.94).

Table 3. Experimental performance metrics.

	ELM	ID-RELM	ID-RELM & RF
Accuracy	0.81	0.88	**0.94**
Sensitivity Healthy	0.89	0.98	**0.98**
Sensitivity Unhealthy	0.74	0.79	**0.93**
Specificity Healthy	0.78	0.82	**0.93**
Specificity Unhealthy	0.88	0.97	**0.98**
F1-measure Healthy	0.83	0.89	**0.95**
F1-measure Unhealthy	0.80	0.87	**0.95**
Number of hidden nodes	153	42	**40**

We now come to compare the obtained diagnosis results from the adapted PHM tool using ID-RELM & RF to several methods that were recently proposed to contribute in developing the decision support system for heart disease diagnosis (see Table 4). It can be observed that ID-RELM & RF improves the performance of CAD for heart disease (accuracy = 0.94). The proposed method do not only improve the accuracy of the system, but it also reduces the processing time (see Table 5). This indicator is a very important factor for real time applications.

5. CONCLUSION

The framework of this paper is to transfer the PHM approach from industrial to medical field. This work could be considered as a first step to reduce the gap between industry and medical fields, by exchanging the applied techniques, and by

Table 4. Performance comparison of our proposed method along with previous work on UCI heart disease Cleveland dataset. Acronyms: ANN: artificial neural network. LR: Logistic regression. SVM: Support vector machine. mRMR: Minimum Redundancy Maximum Relevance. RF: Random forest. NB: Naïve Bays. DT: Decision tree. ID-RELM : Dragging Regularized ELM. RFE : Recursive feature elimination. FAMD: Factor analysis of mixed data.

Previous work	Classifier	Feature selection	Accuracy
(Pahwa & Kumar, 2017)	NB	SVM- RFE/10 F	0.84
	RF	SVM-RFE/8F	0.84
(Pouriyeh et al., 2017)	NB		0.83
	SVM		0.84
	SVM+MLP		0.84
	KNN (k=9)		0.83
	DT		0.77
	MLP		0.82
(Xu et al., 2017)	RF		0.91
(Xu et al., 2017)	Majority vote-based model (NB,DT,SVM)		0.82
(Gupta, Kumar, Arora, & Raman, 2019)	FAMD+RF		0.93
(Tu, Shin, & Shin, 2009)	Bagging with decision tree		0.81
(Bhatla & Jyoti, 2012)	NB		0.86
	ANN		0.85
	DT		0.89
(Atallah & Al-Mousa, 2019)	Hard Voting Ensemble Method		0.90
(Haq, Li, Memon, Nazir, & Sun, 2018)	LR	reflif	0.89
	NB	mRMR	0.84
	SVM	LASSO	0.88
Our approach	ID-RELM	RF	**0.94**

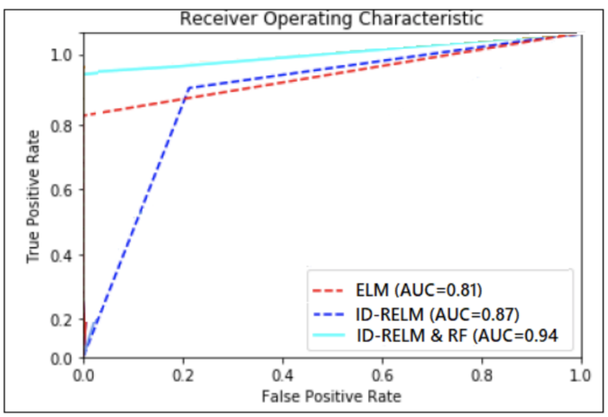

Figure 3. ROC curve of our proposed method.

showing that models applied for machine's health diagnosis could be applicable for human's health diagnosis. The suggested system accomplished higher classification accuracy rate by improving the data quality, decreasing the number of attributes and increasing the performance rate with less processing time. The ID-RELM & RF model can be used as a medical decision support system for cardiologists to make accurate classification with lower time, cost, and effort.

One could think about comparing the performance of our proposed method with MathWorks Predictive Maintenance toolbox to emphasize the effectiveness of the proposed model. The obtained results allow us to think about generalized PHM model using domain adaptation and transfer learning to solve other challenging applications. However, one should keep in mind the complexity of biological system, the lack of medical data availability, and patient's data privacy.

Table 5. Processing time comparison of our proposed method and existed work.

Model used	Processing time (s)
Logistic regression	2.159
K-nearest neighbor	0.144
Artificial neural network	30.802
SVM (kernel=RBF)	60.589
SVM (kernel=linear)	0.179
Naive Bayes	1.596
Decision tree	1.831
Random Forest	2.220
ID-RELM & RF	**0. 07**

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