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Review

# Artificial intelligence for fault diagnosis of rotating machinery: A review

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ABSTRACT

Fault diagnosis of rotating machinery plays a significant role for the reliability and safety of modern industrial systems. As an emerging field in industrial applications and an effective solution for fault recognition, artificial intelligence (AI) techniques have been receiving increasing attention from academia and industry. However, great challenges are met by the AI methods under the different real operating conditions. This paper attempts to present a comprehensive review of AI algorithms in rotating machinery fault diagnosis, from both the views of theory background and industrial applications. A brief introduction of different AI algorithms is presented first, including the following methods: *k*-nearest neighbour, naive Bayes, support vector machine, artificial neural network and deep learning. Then, a broad literature survey of these AI algorithms in industrial applications is given. Finally, the advantages, limitations, practical implications of different AI algorithms, as well as some new research trends, are discussed.



**Contents**



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## 1. Introduction

With the rapid development of technology and science, mechanical equipment in modern industry becomes more and more functional and complex. Rotating machinery is among the most important equipments in modern industrial applications. Fault diagnosis of rotating machinery becomes the most critical aspect in system design and maintenance.

Fault diagnosis of rotating machinery is a technique of fault detection, isolation and identification, which can be used applied on the information about operation condition of the equipment [1]. There are three basic tasks of fault diagnosis: (1) determining whether the equipment is normal or not; (2) finding the incipient failure and its reason; (3) predicting the trend of fault development. Therefore, essentially, fault diagnosis can be regarded as a pattern recognition problem regarding the rotating machinery condition. As a powerful pattern recognition tool, artificial intelligence (AI) has attracted great attention from many researchers and shows promise in rotating machinery fault recognition applications.

Due to the variability and richness of the response signals, it is almost impossible to recognize fault patterns directly. Therefore, a common fault diagnosis system often consists of two key steps: data processing (feature extraction), fault recognition [1,2]. Most common intelligent fault diagnosis systems are built based on the preprocessing by feature extraction algorithms [2] to transform the input patterns so that they can be represented by low-dimensional feature vectors for easier match and comparison [3].

Then, the feature vectors are used as the input of AI techniques for fault recognition. The step of fault recognition amounts to mapping the information obtained in the feature space to machine faults in the fault space. Numerous AI tools or techniques have been used, including convex optimization, mathematical optimization, as well as classification-, statistical learning- and probability-based methods. Specifically, classifiers and statistical learning methods have been widely used in fault diagnosis of rotating machinery, that includes, k-nearest neighbor ($k$-NN) algorithms [4], Bayesian classifier [5], support vector machine (SVM) [6] and artificial neural network (ANN) [7]. Most recently, deep learning approaches have also began to be applied in the field of fault diagnosis [8].

In this paper, we aim at presenting a comprehensive survey on the recent research and development of AI methods for rotating machinery fault diagnosis, from both the views of theory and application. The rest of this paper is organized as follows. Section 2 introduces the basic theory of various AI methods. Section 3 reviews the applications of AI approaches in rotating machinery fault diagnosis. Prospects of AI methods in fault diagnosis are discussed in Section 4. Concluding remarks are drawn in Section 5.

## 2. Theoretical background of AI approaches

AI algorithms for fault diagnosis of rotating machinery have become popular due to their robustness and adaptation capabilities. Also, they do not require full prior physical knowledge, which may be difficult to obtain in practice. Among the various AI algorithms, $k$-NN, Naive Bayes classifier, SVM and ANN algorithms have been applied most commonly in fault diagnosis.

### 2.1. k-Nearest neighbour

$k$-NN is an instance-based learning algorithm based on the principle that the instances within a dataset will generally exist in close proximity to other instances with similar properties [9]. For a given training set of classified instances $T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\}$, where $x_i$ is the feature vector of the unlabeled instance, $y_i$ is the label and $y_i = c_1, c_2, \ldots, c_K,\ i = 1, 2, \ldots N$. For a training sample $(x, y)$, the $k$-NN algorithm searching for the $k$ nearest instances to $x$ based on a given distance metric. The neighbourhood containing these $k$ instances is represented by $N_k(x)$. Then, the label of test sample $x$ can be calculated based on decision rules:

$$y = \arg\max_{c_j} \sum_{x_i \in N_k(x)} I(y_i = c_j), \quad i = 1, 2, \ldots, N; \quad j = 1, 2, \ldots K \tag{1}$$

where $I$ is the indicator function.

If the instances are tagged with a classification label, then the label of an unclassified instance can be determined by observing the class of its nearest neighbours as shown in Fig. 1 [10].