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Comparison of Machine Learning Models and Feature Importance Investigation of Intelligent Fault Diagnosis Methods for Robots Based on Datasets Across Various Distributions

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Abstract:

Intelligent fault detection is an important component of the industrial and automation fields. However, conventional research on intelligent fault detection mainly focuses on industrial production equipment, while there is little research on intelligent fault detection scenarios for robots. Based on a hexapod robot joints dataset, this paper investigates intelligent fault diagnosis tasks in the field of robotics. Firstly, the dataset is clustered into two new datasets with different distributions through k-means method, which is used to simulate the practicality of imbalanced distribution between healthy and fault data. Afterwards, several multioutput machine learning classification models were established to predict robot joints with faults. In two datasets with different distributions, the larger one is used as the training set and the smaller one is used as the testing set. The article compares the performance of these models with prediction accuracy as the main indicator. And based on the results, the paper selects the model with the highest accuracy for further exploration of feature importance. Finally, the article explains the significance of the results and analyzes possible reasons. The experimental results show that the random forest model better overcomes the problem of data distribution differences and has the highest accuracy. In the random forest model, the importance of position data representing position error is higher than that of slope with respect to the axis data representing angle error. This result may be related to the distribution of feature values and the fact that position data contains more crucial information.

Keywords: Machine learning; fault detection; hexapod robot; intelligent manufacturing.

1. Introduction

With the continuous innovation and upgrading of Artificial Intelligence (AI) technology, they are beginning to facilitate an increasing number of tasks and solving more actual problems. One of the main representations is Intelligent Fault Detection (IFD), which refers to using machine learning methods in traditional machine fault detection. This kind of detection method focuses on utilizing machine learning algorithms to adaptively learn the mechanical detection knowledge from the available datasets rather than applying the experience and knowledge of engineers [1, 2]. Well satisfying the needs of intelligent manufacturing, IFD has become a crucial component of industrial and automation areas.

In the past ten years, a lot of scholars studied IFD technologies and reached breakthrough accomplishments on industrial practice especially. For instance, Shubita et al. built a rotating elements fault diagnosis system based on Acoustic Emission (AE) through comparing different machine learning algorithms including fine decision tree [3], SVM, naive Bayes and KNN. Their approach with a fine decision tree ML model can be used on machine condition monitoring and its accuracy achieves 96.1%. S. Quabeck et al. proposed an induction machines fault detection and classification algorithm by combining MSCSA-features as well as the slip information with a KNN algorithm [4], which is effective over a wide operating range and achieves an accuracy of 97.4%. In [5], Vives evaluates traditional approaches and the fault diagnosis for bearings based on the KNN and SVM models, and proves that machine learning is improving the accessibility and reliability of wind turbine fault detection, monitoring, and diagnosis.

In recent years, robot technology, as a product of interdisciplinary between mechanics, automation and computer science, have made considerable progress. The combination of IFD methods and robot technologies has exposed brand-new research potential and exploration value. Christensen et al. establish a generate fault detectors for autonomous mobile robots through fault injection and learning [6]. The detector is actually a neural network to discriminate between normal and faulty operation and even allows one robot to detect faults that occur in another robot. In [7], authors propose a feature extraction module, extracting two motion-insensitive fault features from Short-Time Fourier Transform (STFT) and Hilbert Transform (HT) in both steady and transient states, and apply unsupervised learning algorithms on the extracted features for industrial robot fault detection. It is effective for this framework to detect gear-wear faults in the robot with higher than 96% accuracy. Aiming at fault detection of manipulators, some studies use Neural Networks (NN) and SVM to develop the scheme [8, 9], respectively. Shi et al. construct an Artificial Neural Network (ANN) model for quadrotor robot [10], which receives the residual vector between real measurements as well as estimated measurements and outputs classification results about ten types of faults.

However, in the early study about robot faults detection, researchers did not pay much attention to the differences in data distribution. Actually, due to the collected data from the healthy state are far more sufficient than data from the faults, this imbalance distribution of dataset problem is universal in both industrial and robot working scenarios. Lei et al. suggest that transfer learning may alleviate this problem to a certain extent and propose an idea that IFD using transfer learning in future in [1]. And the authors define transfer learning in IFD as reusing knowledge from one or multiple fault detection or diagnosis tasks to other related but different assignment.

This paper aims to explore intelligent fault diagnosis in robotics. First, the dataset is divided into two new datasets with different distributions using the k-means method to simulate the imbalance between healthy and faulty data. Next, several multi-output machine learning models are developed to predict faults in robot joints. In the two datasets, the larger one serves as the training set, and the smaller one is used for testing. The paper compares the models' performance based on prediction accuracy and selects the most accurate model for further analysis of feature importance.

2. Method

2.1 Dataset Preparation

The dataset used in this study is collected from Kaggle [11]. This dataset contains information on the joints of hexapod robots, which has 145683 objects and comprises 10 columns, with 9 features such as X, Y, Z positional data of the joints and 1 label. Label indicates the state of the joints, with -1 representing all joints being fault-free, '0&1' for faults in the first and second joints, and so on up to '16&17', which sum up to 154 categories. This dataset mainly used in classification tasks, namely what IFD aims to do.

In order to simulate the scenario with distribution diversity, the dataset is first divided into two clusters based on features by k-means algorithm. Then, by matching with the original dataset, the labels corresponding to the objects are stored into two new csv files. Through preprocessing, the original task is transformed into two classification tasks with diverse data distribution, while one has 89, 764 objects, the other has 55, 919 objects. Besides, original labels are split, for example, original "10&12" is separated into two columns including label one "10" and label two "12". Meanwhile, aiming to satisfy the requirement of input data, fault-free label "-1" is duplicated and transformed into two columns. ML models predict and output results for label 1 and label 2 respectively.

2.2 Machine learning-based Prediction

The experiment based on several classical machine learning algorithms, including SVM, KNN, RF, DT and Multilayer Perceptron (MLP). Connecting with a multioutput classifier, ML algorithms perform IFD task and output prediction results for two labels separately. Indicators for the evaluation include accuracy, precision, recall, F1 score and confusion matrix. After comparing the performance of models, experiment further explored feature importance of well-performed ML model. Following the experience, the dataset having 89, 764 items is used for training, and the other dataset is used for prediction task.

2.2.1 Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning algorithm, widely used in classification and regression tasks. The principle of SVM is finding the optimal hyperplane that best separates different classes in the feature space. Aiming to maximize the margin between classes, model regards data points closest to the decision boundary as support vector. By utilizing kernels, SVM can effectively handle non-linear data by mapping it to a higher-dimensional space. It is due to its versatility and ability to handle complex datasets, SVM has been employed in countless domains.

2.2.2 K-Nearest Neighbors

K-Nearest Neighbors (KNN) is a simple and effective machine learning algorithm used for classification and regression tasks. It identifies the k-nearest data points in the training set to a given query point and assigns a label based on the majority class among these neighbors. KNN does not make assumption of about the underlying data distribution and defers computation until operates classification. KNN has a good interpretability, while its performance is sensitive to the choice of k and data dimensionality.

2.2.3 Multilayer Perceptron

Multilayer Perceptron (MLP) is a type of artificial neural network composed of multiple layers of nodes; each layer connected to the next. It employs nonlinear activation functions to process data and learn complex patterns. MLP is a versatile model used for both regression and classification tasks, capable of approximating any continuous function given enough data and training time. By adjusting the number of layers and nodes, along with hyperparameters like learning rate and regularization, MLP can be tailored to different datasets and display strong performance in various domains such as image recognition, natural language processing, and more. The structure of MLP is a single hidden layer containing four neurons.

2.2.4 Decision Tree

Decision Trees (DT) are hierarchical tree-like structures used in machine learning for classification and regression tasks. They recursively split the dataset based on feature values to create branches representing decision paths. Each internal node corresponds to a feature, and each leaf node represents a class label or numerical value. DTs are interpretable models that can handle both numerical and categorical data, making it popular for its simplicity and ability to capture complex decision boundaries. However, DT is prone to overfitting and requires techniques like pruning to promote generalization on unknown data sometimes.

2.2.5 Random Forest

Random Forest (RF) is an ensemble learning method that constructs a multitude of decision trees during training. Each tree in the forest is trained on a random subset of the data and features, and predictions are made by aggregating the outputs of individual trees (like averaging for regression or voting for classification). Compared with individual DT, RF is known for its robustness against overfitting, ability to handle high-dimensional data, and effectiveness in capturing complex relationships in the data. It has been widely used in various fields such as classification, regression, feature selection, and fault detection especially.

Feature importance evaluation is a significant property of RF, which helps to determine optimal feature set and further enhances accuracy of models. Feature importance evaluation on RF is defined as computing contribution value of each feature in each tree [12]. The average of the contribution values is served to measure the importance of a feature. Function Feature importances_, in sklearn package of python, can be applied on analyzing feature importance and generate normalized importance values.

3. Results and Discussion

3.1 Performance Comparison of Fundamental ML Models

In this study, K-means model is responsible for separating original dataset into two clusters with different data distribution. Through Principal Component Analysis (PCA) processing, the dimensionalities of primary features were reduced, which were transformed into two brand-new components. Visualization of the dimensionality reduction results is in Fig. 1. Through Fig. 1, the data distribution of the two datasets is approximated by two vertical lines, which proves the distribution difference between new datasets.

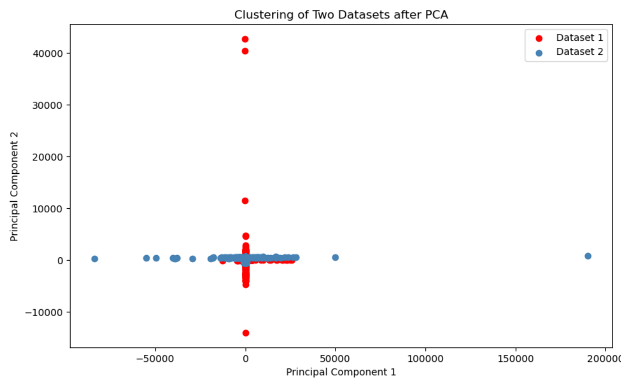

Fig. 1 Clustering of two datasets after PCA (Photo/Picture credit: Original).

By using RBF kernel and setting the value of the penalty to 1, SVM model is established. Through multilayer classifier, the prediction accuracy for label 1 is 12%, while for label 2 is 13%.

As for KNN model, the model accuracy results according to neighbour value range from 1 to 30 are visualized through python drawing function. The results are displayed in Fig. 2.

Fig. 2 KNN accuracy with value of neighbours (Photo/Picture credit: Original).

According to Fig. 2, considering overall results, when neighbours value equals to 21, the prediction accuracy of label 1 up to 23.6%, while the other accuracy for label 2 is 25.7%. At this point, the KNN model exhibits best performance.

For MLP model, one hidden layer with diverse number of neurons network frameworks is explored. From one neuron to nineteen neurons, under the condition that the maximum number of iterations is 500, the variations in model accuracy are as Fig. 3 shows.

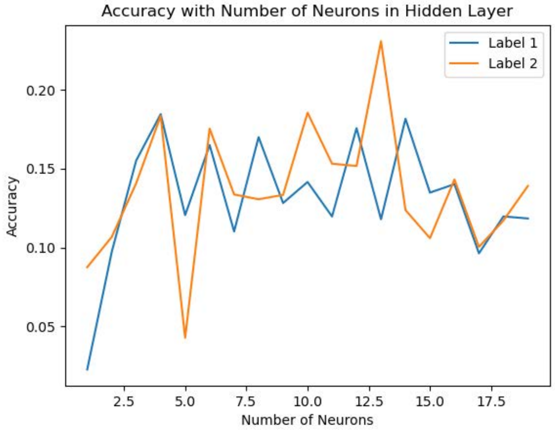

Fig. 3 MLP accuracy with Number of Neurons in one hidden layer (Photo/Picture credit: Original).

Weighing the accuracy of two labels, the MLP model achieved the best performance when the number of neurons is 4. While prediction accuracy for label 1 is 0.18, and prediction accuracy for label 2 is 0.18.

Applying DT model on these different distribution datasets and max depth of the tree is 15, the prediction accuracy of label 1 up to 98%, and for label 2 is 98%.

Utilizing RF model for experiment, the number of trees is 11 and max depth of each tree is 10, RF model also displays a good performance on this task, for label 1 accuracy is 99% and label 2 accuracy is 98%.

In the end, the performance of the above five machine learning classification models on robot IFD tasks is summarized and drawn as a bar chart, which is shown in Fig. 4.

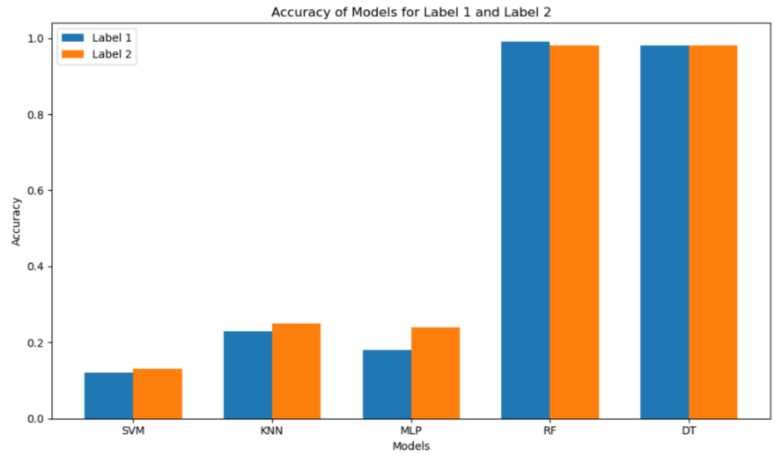

Fig. 4 Performance comparison of above five ML models (Photo/Picture credit: Original).

According to Fig. 4, RF and DT multi output models demonstrate strong performance in IFD tasks. They are good options for overcoming the diversity of distribution. In contrast, SVM, KNN, and MLP seem unsatisfactory in on the other dataset with different distribution.

As an integrated learning method, RF obtains prediction result through voting or calculating the average, which allows RF to have an accuracy preponderance over single DT and avoids depth of trees being too great. Selecting features randomly, RF has robustness to abnormal values, noise and overfitting problem. The robustness helps model to overcome the distribution diversity of training set and testing set. Also, based on tree models, RF does not need strict data preprocessing like feature scaling or standardization and has enough interpretability. It is worth mentioning that randomness of RF reduces the relevance of features in analysis process and increases the necessity of feature importance exploration. For example, Yu et al. sort the features of mechanomyography signal according to feature importance from RF method in [12].

3.2 Feature Importance of RF

Due to outstanding capacity of solving IFD tasks on the collected dataset. This paper also makes further exploration of feature importance of RF model, in order to figure out which feature has the greatest influence on RF model performance and improve the model reasonably.

By using permutation importance function provided, the features importance as numerical values could be evaluated. For nine features in the training set, the analysis results of feature importance are shown in Fig. 5.

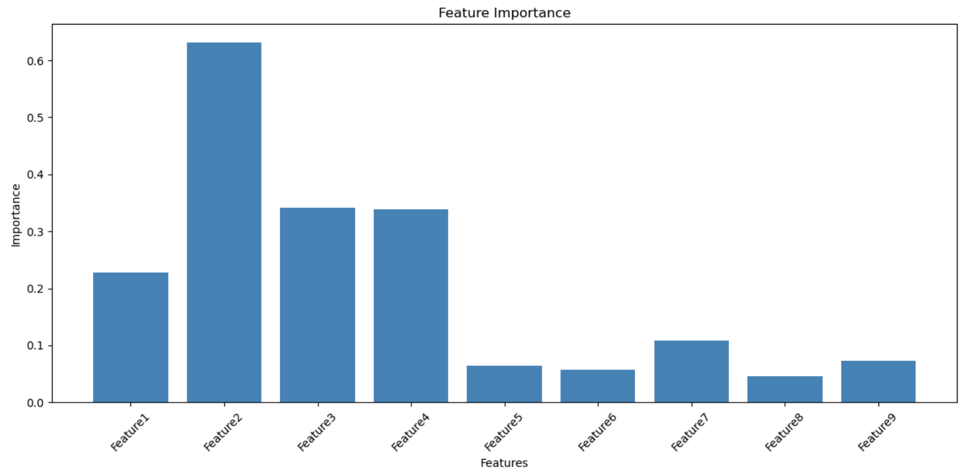

Fig. 5 Feature importance of nine features in training set (Photo/Picture credit: Original).

From the bar chart, the most important feature is feature 2, which refers to Y positional data of the joints. Other features, such as feature 3 and 4, referring to Z positional data of joints and slope with respect to the x-axis respectively, are also crucial to the prediction results. The X positional data represented by feature 1 is not negligible for RF model. Other features are indifferent in this robot IFD scenario for RF method.

Joints of robots are usually controlled by motors or steering engines. Angle error and position error are potential indicators in fault detection methods for robot joints, such as [13]. In the features of selected dataset, positional data can reflect position error, and other slope values can reflect angle error. According to the feature importance result, RF prediction model is more sensitive to position error than angle error in this hexapod robot IFD scenario. The possible reason is that the distribution and variation range of position data are wider than slope data represented by tangent values. The positioning error of robot joints may be affected by various factors, such as the kinematic and dynamic parameters of the robot, which may be more critical for fault detection. Thus, compared with angle data, position data is a more decisive and more prominent factor in normal IFD tasks.

4. Conclusion

In this paper, the study focuses on robot joints fault detection scenarios and compares several ML classification models performance on simulation of different distribution datasets. For models with the best performance, the paper further investigate the importance of features. Experimental results showed that RF model demonstrate adaptability to differences in data distribution and their prediction accuracy is close to one hundred percents. Besides, positional data of joints have a considerable influence on prediction results of RF model. Nevertheless, the experimental results have limitations for minor adjustments to the model structure. In the further work, there is still wild field for researchers to find competent algorithm and fill the gaps in the field of robot IFD on the basis of feature importance outcome in this paper.

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