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Machine Predictive Maintenance by Using Support Vector Machines

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Abstract: Predictive Maintenance (PdM) is an adoptable worth strategy when we deal with the maintenance business, due to a necessity of minimizing stop time into a minimum and reduce expenses. Recently, the research of PdM is now begin in utilizing the artificial intelligence by using the machine data itself and sensors. Data collected then analyzed and modelled so that the decision can be made for the near and next future. One of the popular artificial intelligences in handling such classification problem is Support Vector Machines (SVM). The purpose of the study is to detect machine failure by using the SVM model. The study is using database approach from the model of Machine Learning. The data collection comes from the sensors installed on the machine itself, so that it can predict the failure of machine function. The study also to test the performance and seek for the best parameter value for building a detection model of machine predictive maintenance The result shows based on dataset AI4I 2020 Predictive Maintenance, SVM is able to detect machine failure with the accuracy of 80%.

Keywords: Predictive Maintenance; SVM; Machine Failure; AI.

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1. Introduction

Predictive Maintenance (PdM), used to say as "on-line monitoring", "risk-based maintenance" or "condition-based maintenance", is recently a common topic of many research papers. It refers to a smart monitoring system to avoid future failure. Predictive Maintenance have evolved from its initial concept into an automation methods using artificial intelligence based on pattern recognition, machine learning, neural networking and fuzzy logic etc. Automation methods give more proper solutions to many industries which continuously 24/7 detect and collect information which human's eye or ear cannot do. With the combination of integrated sensors, predictive maintenance can be carried out in avoiding unnecessary part replacement, reducing stop time, root cause analysis also saving expenses and improve efficiency.

Predictive Maintenance have overlapping tendency with the concept of preventive maintenance on its activity scheduling. The difference with conventional preventive maintenance is that the activity schedule of predictive maintenance is based on the data collection from sensor and algorithm analysis [1]. Predictive Maintenance have two main focuses: energy efficiency improvement (energy saving focus) and the decrease of unscheduled stop time. Related studies with the predictive maintenance are 1) method and equipment innovation in energy evaluation [2], 2) condition system monitoring include machine failure detection, with many various artificial intelligence techniques [3], [4].

One popular approach taken in predictive maintenance is database approach. It is so called data mining or machine learning approach which is using historical data to study the system behavior model. This model-based approach has capability in combining the physical understanding of the target product and relies on the analytical model that represent the system. Many studies have been done recently, [1], [3]–[7]. However not all data can utilize existing machine learning so that the potentiality of various machine learning methods utilization is so widely open. On of the famous method in classifying is the method of Support Vector Machines (SVM).

The article present PdM methodology based on machine learning. PdM purpose is to early detect the machine failure using artificial intelligence. Model used is SVM. The study use database approach with Machine Learning model sourced from sensors installed in the machine. The study also measures machine learning performance used and seeking the best parameters can be used for building a detection model in its predictive machine maintenance.

2. Materials and Experiment Methods

Support Vector Machine

Experimental method used is Support Vector Machine (SVM). SVM is an algorithm of machine learning to analyze data for classification and linear regression. SVM is a controlled learning method which observe data and sort them into one of two categories. It produces data map sorted out with a safety margin. SVM used when we want to categorize text, picture classification, handwriting recognition and other science applications.

Main goals of SVM algorithm are to categorize every new data input. It makes SVM a linier nonbinary classifier. SVM Algorithm supposed not to just put an object into a category, but also networking a safety wide margin between them in graphics.

SVM implemented in many classification fields, see Fig [8], [9], medics [10], [11], engineering [12], [13] etc. SVM gives good accuracy in many applied fields, so it become one of the popular classification methods. In this study, the author conducted machine failure detection using SVM method and observe the performance result.

Dataset

Dataset used in the study is the open data sourced from UCI Machine Learning titled dataset AI4I 2020 Predictive Maintenance [3], [4], [14]. This dataset composed of 10.000 data point stored as rows within 14 features in columns. In the research we restrict the data used. The study utilizes 6000 data with low type. 5 (five) features used in the study which are ambient temperature (K), process temperature (K), rotation velocity (RPM), the torque (Nm) and wear and tear ability (min) with the classification target number 0 and 1, where 1 is a symbol to describe machine failure. Comes into attention is unequal amount between 0 and 1 target which lead us to utilize under sampling data.

The details related to the features used in the study are as follows:

1. Product ID: consist of letter L, M, or H for low (50% of all products), medium (30%) and high (20%) as the variable of product quality and serial product number.
2. Ambient temperature [K]: occurred from random walk process normalized to a deviation standard 2 K, defined as 300 K.
3. Process temperature [K]: produced from scattered process normalized to a deviation standard 1 K, added to the ambient temperature by 10 K.
4. Rotasi velocity [rpm]: measured from 2860 W, covered by normal distribution noise.

5. Torque [Nm]: normal distributed torque value approx. 40 Nm with = 10 Nm dan no negative values.
6. Wear and tear [min]: Quality variant H/M/L by adding 5/3/2 minutes wear and tear of tools used in process And
7. Labelling 'machine failure' which sign whether the machine fail or not in some point for a certain failure mode If at least one of failure modes is true, the failure process and the labelling is set to 1 or vice versa.

3. Results and Discussion

The study explores 2 (two) parameters in building classification model using SVM, which are C and Gamma parameter. The parameter pair tested is C = [0.1,1,10,100,1000] and gamma = [1,0.1,0.01,0.001,0.0001]. Every experiment done by pairing between related C and gamma so that every experiment has combined 25 parameter pairs. The study then seeks for the best pairs. The experiment repeated 5 (five) times for the best accuracy.

Table 1 and Fig 1 describe the result of the experiment. Best average accuracy of 5 experimentation comes from C parameter = 1000 dan Gamma parameter = 0.0001 with the level of accuracy amount of 90%. On the contrary, the lowest average of accuracy comes from parameter value of 1 dan 0.0001 for C dan Gamma. The level of accuracy is only 83%.

Table 1. Experiment result on dataset AI4I 2020 Predictive Maintenance type this is a table.

Experiment	C	Gamma	Accuracy Training Data	Accuracy Testing Data	Average of Accuracy
1	1000	0.0001	0.97	0.88	0.93
2	100	0.0001	0.94	0.83	0.89
3	10	0.0001	0.94	0.81	0.88
4	1000	0.0001	0.98	0.85	0.92
5	1	0.0001	0.87	0.78	0.83

We can see from Figure 1 machine failure detected on data AI4I using SVM method on data training reach the peak on 4th experiment with the value of 98% the followed by experiment 1st with the value of 97% dan 5th experiment with the value of 87%. Along with the data trend the accuracy of data testing also sequenced in a same pattern, except in experiment 1st dan 4th whereas data testing from 1st exceeding the 4th by 3%. This is a figure. Schemes have a different format. If there are more than one panel, they should be listed as follows: **(a)** description of what is in the first panel; **(b)** description of what is in the second panel. Figures should be placed near the first time they are cited in the main text. A single-line caption should be centered.

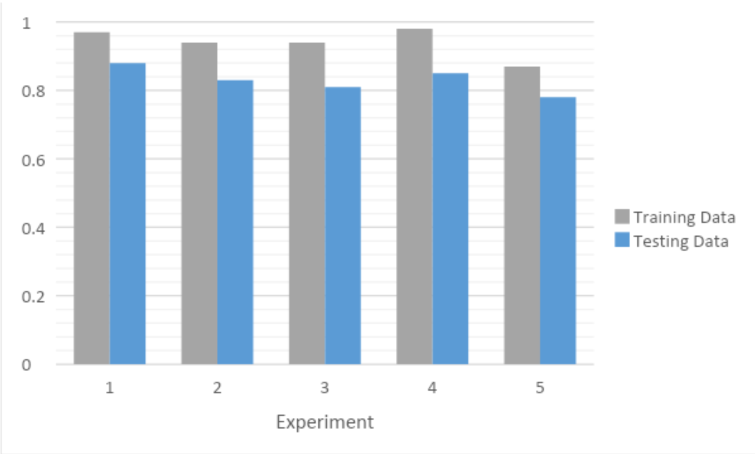

Figure 1. The result of machine failure detection on dataset AI4I 2020 Predictive Maintenance type L

Generally, the overall accuracy result of more than 80% shows that the performance of SVM model is very promising.

4. Conclusions

Based on the experiment result, the best accuracy of all 5 (five) experiment comes from the value of C dan gamma parameters 1000 dan 0.0001 consecutively. While the accuracy model developed for data training is 98% and for data testing is 88%.

In the study, only some part of dataset and just one machine learning model used by the author, which is Support Vector Machines. The study can be extended by testing various machine learning methods such as random forest, neural network, logistic regression et cetera. Besides the study can be developed by using other dataset sourcing from other vehicle or machinery.

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