# Predictive Diagnosis of Machine Failure with Deep Learning Method \*

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The Support Vector Machine (SVM) is known as one of the machine learning method.

SVM requires the skill to design a rule for the feature extraction.

The new method that is not required any technical skills by applying deep learning method is proposed in this paper. The accuracy of machine failure prediction is improved by combining multiple sensor waveform images and extracting features. The new method can be applied to production machines.

Key words :

CNN, Combined image, Predictive Diagnosis

# 1. Introduction

The goal is to develop the predictive diagnosis technology required no technical skill when the algorithm designer adjusts the parameters. Fig. 1 shows the statistics of the machine failures in our company. According to this figure, existing predictive



diagnosis technology does not cover 60% of machine failures.

The diagnosis technology for uncovered area is required to study.

# 2. Conventional Method

Fig. 2 shows the experimental unit to analyze machine failures. The unit consists of motor, bearing, spindle and coupling. Bearings is key parts to assure the machine accuracy. Therefore, the predictive diagnosis technology for bearings is developed.

In Fig. 3, d is the ball diameter. D is the pitch circle diameter. Z is the number of ball.  $\alpha$  is the contact angle.  $f_0$  is the frequency of inner ring rotation. The vibration frecency occured by scratch for each part of bearing can be calculated with these formulas.

The pallets transfer system is widely installed to

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convey workpieces in a transfer line. The pallets collide with each other and large vibration occurs constantly. Therefore, the result calculated by formula in Fig. 3 is not reliable.

There is another conventional predictive diagnosis technology that is the Support Vector Machine (SVM). SVM is one of the supervised learning methods. The SVM classifier is trained by training data. Constructed classifier assigns data into one category or the other. When SVM is applied to the predictive diagnosis of machine failure, the training data is the data measured when the machine has no failure and failure. Fig. 4 shows the SVM concept. SVM calculates the boundary that separates the data without failure and the data with failure. A measured data is classified by calculated boundary. Fig. 5 shows the example of SVM flowchart. In this flowchart, the maximum torque and the minimum torque of servo motor are selected as feature. Fiq. 6 shows the result when executing SVM program. The program is developed with SVM library LIBSVM  $^{2)}$ and image processing library Open CV<sup>3)</sup>.



Fig. 2 Experimental unit

Innner ring scratch =  $\frac{zf_0}{2}(1 + \frac{d}{D}\cos\alpha)$ Outer ring scratch =  $\frac{zf_0}{2}(1 - \frac{d}{D}\cos\alpha)$ Ball scratch =  $\frac{f_0D}{2d}(1 - \frac{d^2}{D^2}\cos^2\alpha)$ Retainer damage =  $\frac{f_0}{2}(1 - \frac{d}{D}\cos\alpha)$ 

Fig. 3 Formula of fault discrimination by frequency



Fig. 6 SVM for predictive diagnosis of servo motor

## 3. Problem

The SVM prediction requires to extract features. Therefore, the algorithm designer is required the skill to select features.

## 4. New Method

To solve above problem, the new method utilizing Convolutional Neural Network (CNN)<sup>4)</sup> is proposed. CNN is one of famous deep learning method, most commonly applied to image analysis. CNN has multiple layered network models which consist of artificial neurons shown in **Fig. 7**. Artificial neurons extract features in the learning process. The feature selection performed by an algorithm designer can be eliminated due to this property. Therefore, the new method is not required specialized skills to select features.

CNN consists of the convolutional layer and the pooling layer, and their process is shown in Fig. 8.

The role of convolutional layer is to extract features from input image. This layer extracts specific graphic components. The role of pooling layer is to summarize features extracted by convolutional layer and to compress them. This layer emphasizes information robustness against misalignment. The fully connected layer consists of input layer, hidden layer and output layer.

Fig. 9 shows the example of fully connected layer which has two hidden layers with three neurons. The function complexity represented by the network depends on the number of hidden layer.

Fig. 10 shows the example of flowchart applying CNN to classify slider without wearing and with wearing. In the case of the predictive diagnosis, an input to CNN is a sensor waveform image. The data is the waveform images of sensors installed in the machine. Especially, the training data is sensor waveform images when the

machine runs without failure and with failure.

The trained network classifies the data when the machine has no failure or failure. The input of CNN requires a single image. The concept of the new method is to combine multiple sensor waveform images.







Fig. 8 Convolutional and pooling layer



Fig. 9 Fully connected layer



Fig. 10 Deep Learning flow chart

Fig. 11 shows the process to combine multiple images. First, the sensor waveforms are transformed with FFT, Wavelet transform and others. Next, transformed images are combined to be a single image. This image generation can achieve to input some sensor waveform images to CNN. Fig. 12 shows the combined images for the slider without wearing (left) and with wearing (right). The difference of waveforms between slider without wearing and with wearing is emphasized by the transformation and combining.

To improve the estimation accuracy of CNN, the combined image is trimmed in this method. Fig. 13 shows combined images before and after trimming.

Fig. 14 shows the flowchart of the new method. This flowchart describes the process of the new method. There is a technical novelty that the deep learning method is applied to the predictive diagnosis of machine failure. The estimation accuracy is expected to be improved by this method.







Fig. 12 Combined images



Fig. 13 Combined image before and after trimming



Fig. 14 Flowchart of New Method

# 5. Verification

### 5.1 Test machine

Fig. 15 shows the test machine structure. The screw transfer unit is installed to convey pallets.

Fig. 16 shows the structure of screw transfer drive unit and the installation position of sensor. The screw is supported by bearings. To detect the drive unit failure, torque sensor, vibration sensor and heat flow sensor are installed on the unit.

The data is collected from these sensors and a PLC.







Fig. 16 Structure of screw transfer drive unit and installation position of sensor

## 5.2 Experiment

To evaluate the accuracy of the new method, we compared the new method with SVM and the random forest by two class classification.

We performed the experiment on the dataset generated while test machine running under different conditions. **Table 1** shows the result of experiment. The score of the new method is higher than conventional methods. Table 1 Result of experiment

	Accuracy	F score
New method	0.966	0.940
Random Forest	0.956	0.918
SVM	0.920	0.921

# 6. Conclusion

The new method to detect machine failure by applying CNN is proposed.

The accuracy of the new method is higher than conventional methods. As a result, the reduction of misjudgment is expected. Therefore, this method can be applied to production machines.

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