WHITEPAPER

Neural Network Detection of Machine Faults

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NEURAL NETWORK DETECTION OF MACHINE FAULTS

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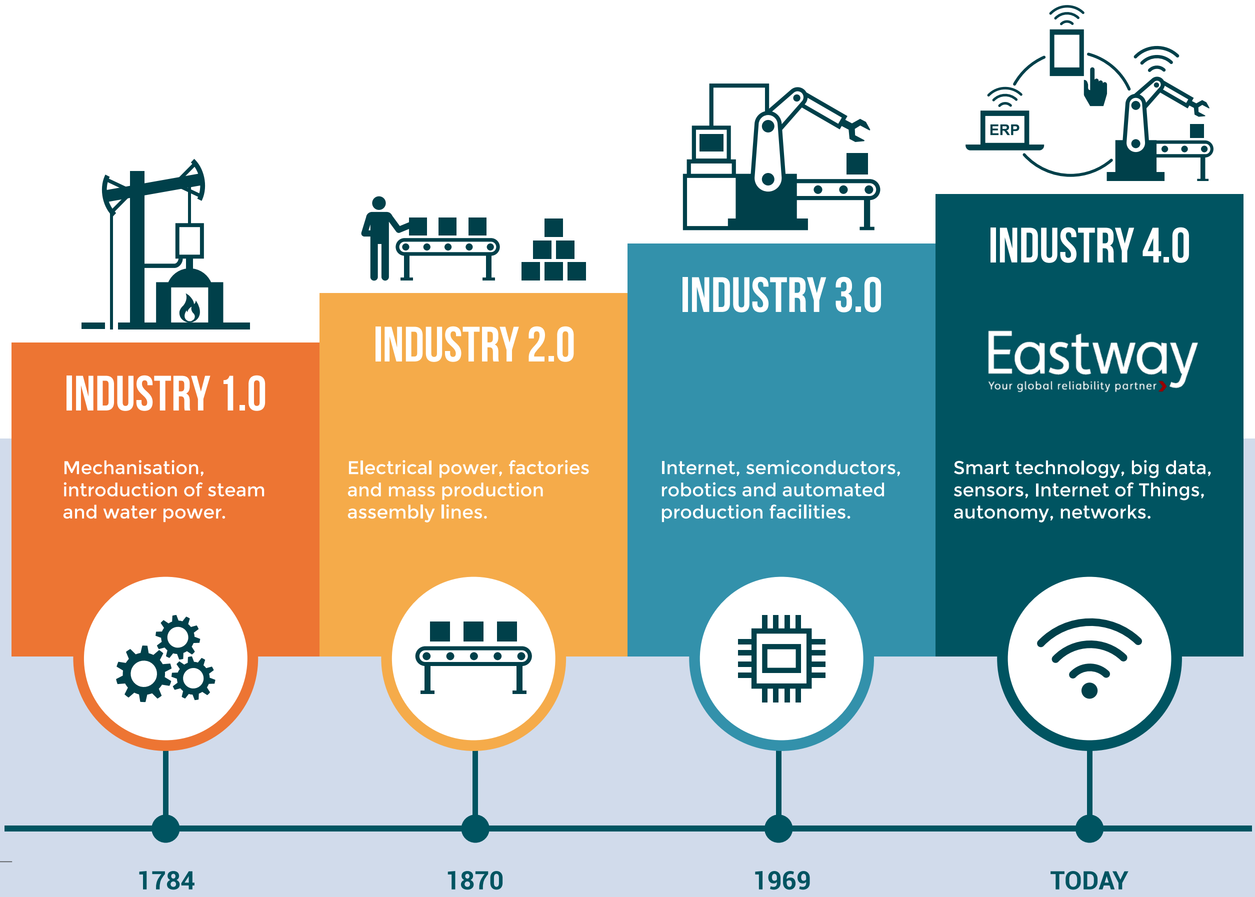
ABSTRACT

We introduce an approach to detect machine faults using vibration sensor data.

Convolutional neural network supervised learning models, trained on Eastway collected and labelled data, demonstrate high levels of performance. The modelling approach is flexible to incorporate further data sources such as machine ambient data, however vibration data may be sufficient given the preliminary results presented here. Furthermore, the approach is adaptable to fault classification upon training with appropriately labelled data.



1. INTRODUCTION

Monitoring of machines via sensor data enables significant savings for plant operators through detection and classification of faults before the occurrence of critical systems failures that may halt production or operations. Berkery and Merrick (2020) discussed anomaly detection with vibration sensor data to raise an alert when a fault is suspected. This paper catalogues further advances in fault detection, including the transfer of learning across vibration sensors and different machine types, the use of neural networks, and a unique and comprehensive dataset of real world machine vibration and performance. The improved fault detection approach is also amenable to extension to fault classification.

We now outline a universal model, trained on real world machine data across a range of different machine types and operating characteristics, that can be applied to any vibration condition monitoring sensor on a machine it has not observed before, for a high level of fault detection.

2. APPROACH

We reached the approach outlined following expert analysis of the problem, trial and error, and a review of the literature. The adopted approach harnesses recent advances in computer vision through deep learning methods, through the preparation of data in such a way that a convolutional neural network may be trained on labelled faults in vibration data.

2.1. DATA

2.1.1. RAW DATA

Historic vibration sensor data (root mean squared of acceleration amplitude) was labelled by expert analysts to identify historically observed faults. Eastway Technical have developed an innovative software-assisted fault labelling system for rapid and efficient labelling.

Data was obtained from vibration sensors monitoring a range of different machine types and operating characteristics, with all machines consisting of an electric motor drive connected to some configuration of machine components. The operating characteristics consisted of both regular cycle, and irregular on-demand, continuous running patterns from both fixed and variable speed motors. Each sensor stream contained 2 to 3 years of labelled data, comprising both good and fault condition machine states. The data was split into Training and Evaluation datasets. The types of machines contained in each dataset are outlined in Table 1.

	Air Handling Units	Pumps	Gearboxes	Dryers	Tower Fans	Compressor	Machine w/ Driveshafts
Training Dataset	79	10	8	5	4	0	2
Evaluation Dataset	21	19	10	2	0	3	0

Table 1: Machine types in dataset

A total of 316 and 156 sensors were used for training and evaluation respectively. The entire dataset contains 5.48 million acceleration vibration readings. Air handling units, a common and often critical machine in industrial processes, accounted for 73.1% of the machines in the training dataset.

2.1.2. DATA PREPARATION

To prepare the data in a format favourable to image recognition neural networks, the ‘vibration map’ method used by Hoang & Kang (2019) is employed. Figure 1 below shows the translation from time series data to vibration map format. There are design choices around appropriate dimensions of the vibration map, and the degree of overlap across maps. As real time data is streamed in, we employ a rolling window method where new data enters at top right of the image, while old data departs at the top left.

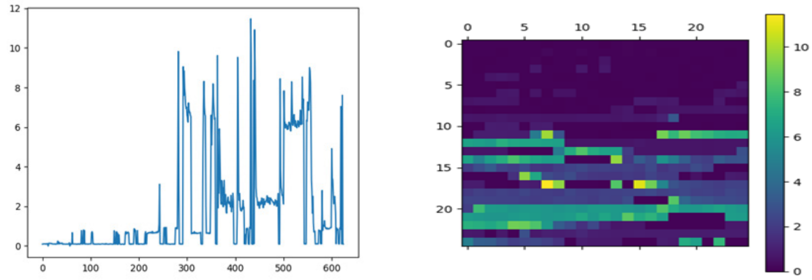


Figure 1: Vibration Map (right) representation of time series (left). Map displays chronological information top to bottom, left to right, as in reading a page

To train or use a model across multiple sensors or machines, and fully harness available data, normalization of data is important. We employ Z-score normalization, where each data point is represented as the number of local standard deviations (positive or negative) from the local mean.

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2.2. MODELLING APPROACH

With each new rolling window, the neural net makes a prediction whether a fault is detected or not, and in the case of classification also predicts what type of fault.

2.2.1. MODEL ACROSS A SENSOR

For a model across a sensor, we may train a 2D convolutional neural network. Such a model sees a vibration map as displayed in Figure 1 above, but considered as a grayscale image, with one value representing the greyscale colour of each pixel.[1]

For our first investigation of neural networks for fault detection purposes, we train across all sensors, with data normalized for comparability. That is, historical data from each sensor across each machine is treated as a series of rolling windows to train upon. One challenge in the implementation of this approach is differing time resolutions across sensors. For example, some sensors may be sampled daily and others hourly. At first implementation, the number of elements in a window is kept fixed, meaning that a 100 block window (fed into the same model) may represent 100 hours or 100 days.

1 In real world applications, individual machines tend to be monitored by multiple sensors. To classify some faults on a machine, patterns across multiple sensors on that machine may provide useful information. To train a machine level model, we can deploy a 3D convolutional neural network, with the 3rd dimension comprising the number of sensors across a machine.

The depth and width of the neural net were chosen on the basis of both judgement and trial & error. Further hyperparameter tuning of the model may yield some degree of performance improvement.

2.2.2. MODEL EVALUATION

The rolling window approach presents a challenge to the model's performance evaluation. For example, if a fault is missed in a window, it is less serious if it is picked up in an adjoining rolling window.

The neural net model produces a fault prediction between 0 and 1, representing no fault and fault respectively, for each rolling window across a sensor stream. An output prediction value of 0.85 or higher was considered a fault condition, while an output value of 0.5 or lower was considered a no-fault condition (Table 2). Predicted outputs in the test and validation set were compared to actual fault events to determine the performance of the model.

Model output, Y	Prediction
0 < y <= 0.5	Machine in good condition
0.5 < y <= 0.85	Undetermined state
0.85 < y <= 1	Fault condition

Table 2: Machine fault threshold values

3. PERFORMANCE RESULTS

Of the 156 sensors evaluated 146 were diagnosed correctly, producing an overall sensor error rate of 0.064. Each sensor with a detection error reported one error only. Of these 10 errors, 9 were false positives and 1 was a false negative. Table 3 outlines the results. Sensitivity can thus be calculated as 17/18 = 94.45% and Specificity estimated as ~1000/(~1000+9) = >99%. [1]

	Definition	Number
True Positive	Fault correctly detected in any rolling window	17
False Positive	Fault incorrectly detected in any rolling window	9
True Negative	Correctly no fault detected	>1000, depends on definition
False Negative	Fault not detected in any rolling window	1

Table 3: Performance reporting

1 The number of True Negatives can be defined multiple ways - for example some duration of vibration data with no fault present, or alternatively a more restricted definition would be any abnormal behaviour in vibration data that was not due to a fault.

Relative to the scale of the evaluation dataset (156 sensors over multiple years of data), there were a low number of faults (18). This fault to data ratio illustrates the low-frequency high-value characteristic of the faults we wish to detect. To this point, it is worth noting that in the False Negative case where the fault condition was not detected, the model predicted an output value between 0.5 and 0.85 ("undetermined state" - see Table 2) but failed to reach the threshold value for fault detection.

Figure 2 shows an example of a fault condition successfully detected. In addition to the red marks indicating a fault, note that preceding the fault the model correctly predicted good condition (green marks), despite spikes due to noise or external factors.

As a final example, it was observed during the analysis the large degree to which two machines of the same type, even on the same manufacturing site, could vary in their operation over time. Despite this underlying variability in the vibration data, the model was able to accurately identify when one set of changes in the vibration data was due to a fault, and only due to the underlying operation variability.

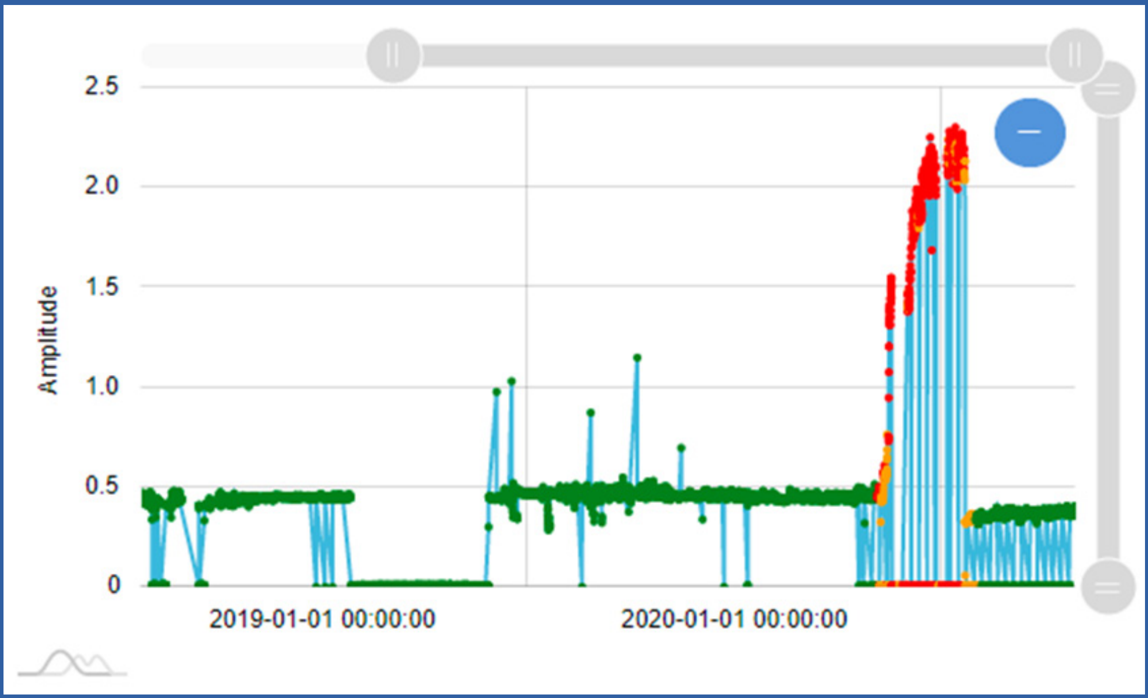

Figure 2: Air Handling Unit vibration data with detected fault highlighted in red

4. CONCLUSIONS

We present methods and findings for detection of machine faults through the use of neural networks on vibration data. The training and evaluation datasets comprised over 5 million vibration readings, obtained from machines spanning a wide variety of machine types and operating environments. Our findings included:

- Accurate fault detection on machines not seen in model training
- A low overall sensor error rate, and a reported sensitivity of 94% and a specificity of 99%

The sensitivity finding was developed on a low number of faults in our datasets. As this system is increasingly rolled out, with new training and evaluation datasets from real world machines, it will be evaluated on an increasing number of faults, increasing the confidence in the detection sensitivity number. The Eastway data collection and labelling infrastructure is designed to efficiently incorporate this data.

Future work includes further turning of the model, both hyperparameter tuning of the neural network model itself, and adjustment of the fault threshold values. Furthermore, the modelling approach may be extended to classify fault types in addition to the identification of faults as discussed here.

REFERENCES

Berkery, Kevin and Merrick, James (2020). Automating Overall Vibration Monitoring with Machine Learning.

Hoang, Duy-Tang and Kang, Hee-Jun (2019). Rolling element bearing fault diagnosis using convolutional neural network and vibration image. Cognitive Systems Research 53, pp. 42-50.

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