Oil-injection Screw Compressor Fault Classification with the help of Short Time Fourier Transform Spectrograms

1. Introduction

Fault prognosis and diagnosis of Machines has become an important subject in the field of Mechanical Engineering. Early prediction and diagnosis can help industries to be more productive and economical. Prognosis and Diagnosis has become an integral part of Industry 4.0.

In this report, a Screw Compressor Fault Classification is done with the help of Convolution Neural Networks by using Short Time Fourier Transform Spectrograms. Spectrograms are created with the help of vibration data from motor and screw compressor. A total of five classes are classified

2. Data

The data is obtained from PHM 2021 Asia Pacific Data Challenge. It contains the vibration data of an oil-injection screw compressor under various normal and fault conditions. Vibration data from Motor and Screw are sampled at 10544 samples per second. A total of 5 classes of operations were made among which has 1 normal condition and 4 abnormal conditions.

The system information is as follows:

<u>Equipment:</u>

- Equipment: Oil-injection screw compressor.
- Motor: 15kW
- Axis rotating speed of Motor: 3,600 rpm
- Axis rotating speed of Screw: 7,200 rpm

<u>Data Acquisition:</u>

- Sampling rate of Data Acquisition: 10,544 samples per second
- Output Channels:
    1. Channel 1: Measuring vibration from Motor
    2. Channel 2: Measuring vibration from Screw

<u>Description of five Classes of operations:</u>

- Normal: Fault-free operating condition.
- Unbalance: Unbalance between centres of mass and axis.
- Belt-Looseness: Looseness of V-belt connecting between motor pully and screw pulley.
- Belt-Looseness High: High Looseness of V-belt
- Bearing fault: Removing grease of Ball Bearing on Motor, which induces its wear-out.

There are 10 CSV files of 5 classes. 2 files are normal condition files, 2 files are belt-looseness files, 1 file is belt-looseness-high file, 3 unbalance condition file, and 2 files are bearing-fault condition files.

3. Methodology

3.1 Data Pre-Processing:

The time series vibration data has to be converted to spectrograms by the process of Short Time Fourier Transform. The time series data is first normalized to the range of -1 to 1.

3.1.1 Data Split

Each file has 2 columns of vibration data from motor and screw. So, 75% of data is split as training data, 23% of data is split as validation data and 2% as testing data.

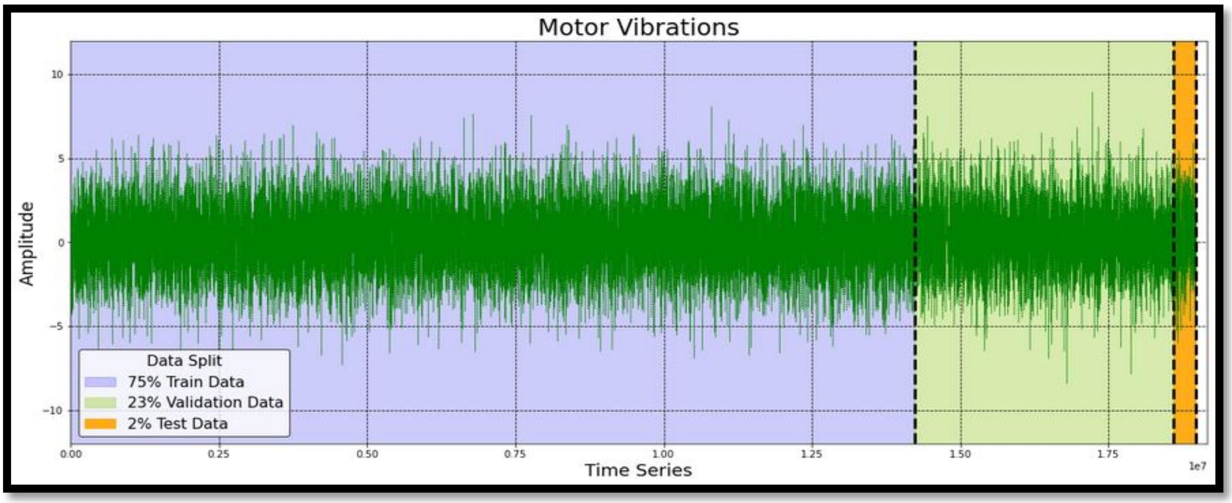


Figure 1. Motor Vibration Data Split

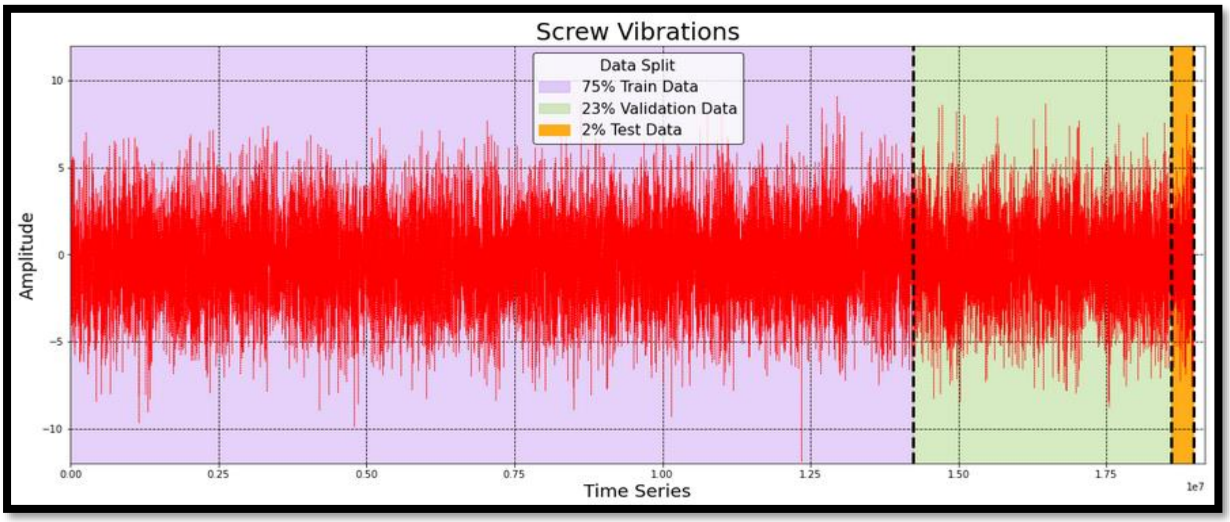


Figure 2. Screw Compressor Vibration Data Split.

3.1.2 Short Time Fourier Transform Spectrograms

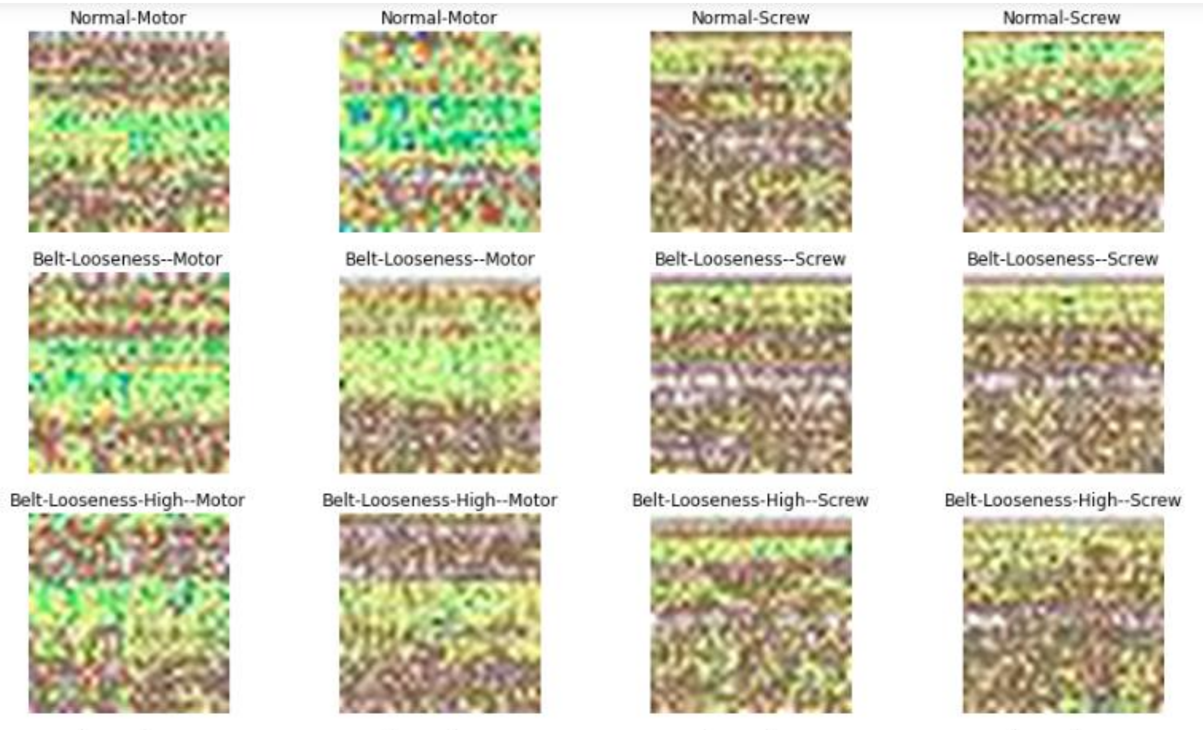
3.2 Deep Learning

4. Analysis

4.1 Spectrogram Generation

The spectrograms are generated by the method described in section 3.1. A code without using any standard library for generating spectrograms is written. The images generated are very similar to the images generated by standard packages producing spectrograms. Spectrograms are generated for both Motor and Screw Vibration data. The spectrograms have a “terrain” colormap.

A total of 2,31,644 images of 32 x 32 size spectrograms were generated. Among them 173752 images belong to training set, 53270 images belong to validation set and 4622 images belong to test set.



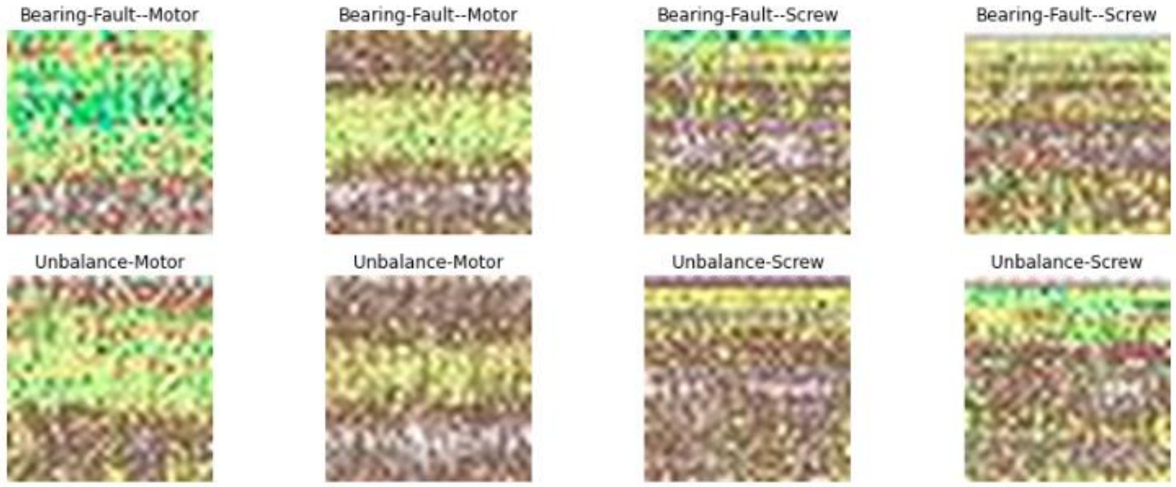


Figure 3. Sample of Spectrograms which are used for classification.

4.2 Neural Network Model

Using TensorFlow's Keras Library the model is defined as per the architecture mentioned in Section 3.2. The training and validation set is fed to the model. A sequential model is used. The model is compiled with Adam Optimizer, Sparse Categorical Crossentropy Loss Function and Sparse Categorical Accuracy Metrics. The CSV logger callback is called to monitor the losses and metrics for future reference.

```
Model: "Screw_Compressor_Fault_Classifier"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
Rescaler (Rescaling)         (None, 32, 32, 3)         0
_________________________________________________________________
Conv_1 (Conv2D)              (None, 32, 32, 64)        1792
_________________________________________________________________
Pool_1 (MaxPooling2D)        (None, 16, 16, 64)        0
_________________________________________________________________
Conv_2 (Conv2D)              (None, 16, 16, 32)        18464
_________________________________________________________________
Pool_2 (MaxPooling2D)        (None, 8, 8, 32)          0
_________________________________________________________________
Flatten (Flatten)            (None, 2048)              0
_________________________________________________________________
Dense_1 (Dense)              (None, 128)               262272
_________________________________________________________________
Dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
Dense_2 (Dense)              (None, 32)                4128
_________________________________________________________________
Dropout_2 (Dropout)          (None, 32)                0
_________________________________________________________________
Dense_3 (Dense)              (None, 16)                528
_________________________________________________________________
Classifier (Dense)           (None, 5)                 85
=================================================================
Total params: 287,269
Trainable params: 287,269
Non-trainable params: 0
```

Figure 4. Summary of the Model.

The model was trained for 10 epochs and the following table describes the change in losses and accuracy.

Epochs	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
0	0.442127	0.830327	0.108316	0.960935
1	0.137587	0.953906	0.069795	0.975108
2	0.093692	0.968628	0.049773	0.983424
3	0.076546	0.974521	0.048833	0.983349
4	0.063486	0.978607	0.039693	0.987272
5	0.058346	0.980944	0.037133	0.987216
6	0.050184	0.983569	0.055352	0.982279
7	0.046943	0.984518	0.031497	0.9893
8	0.043187	0.985479	0.037156	0.98761
9	0.04068	0.986475	0.028724	0.990839

The training accuracy and validation accuracy at the end of epoch was 98.64 % and 99.08 %. The model was finally saved for future usage.

Given below are the Loss and Accuracy variation at different epochs which gives us an idea of training process

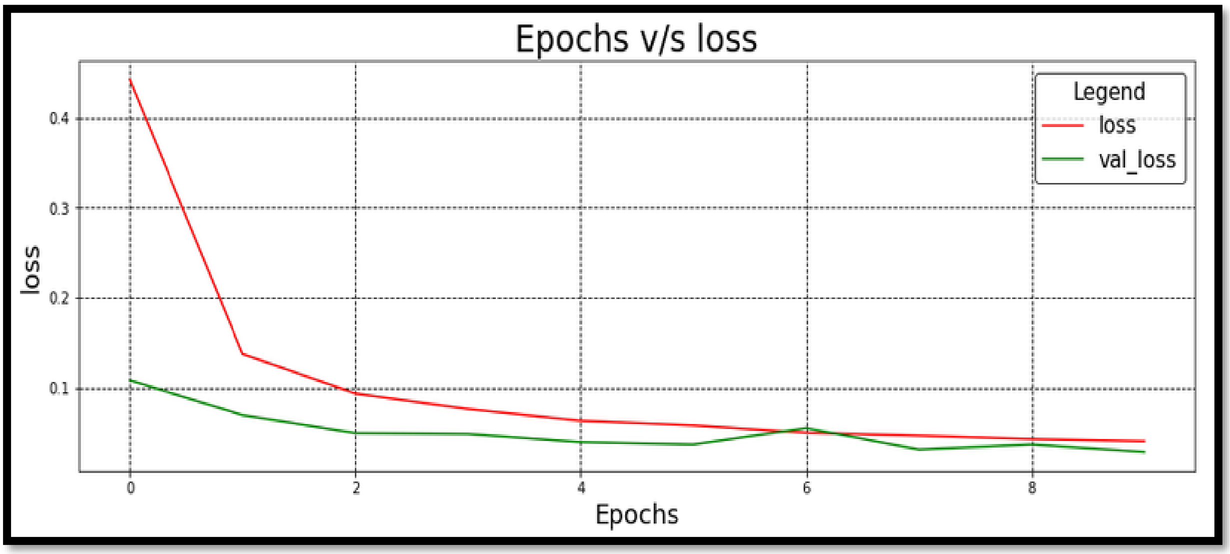


Figure 5. Losses at different epochs.

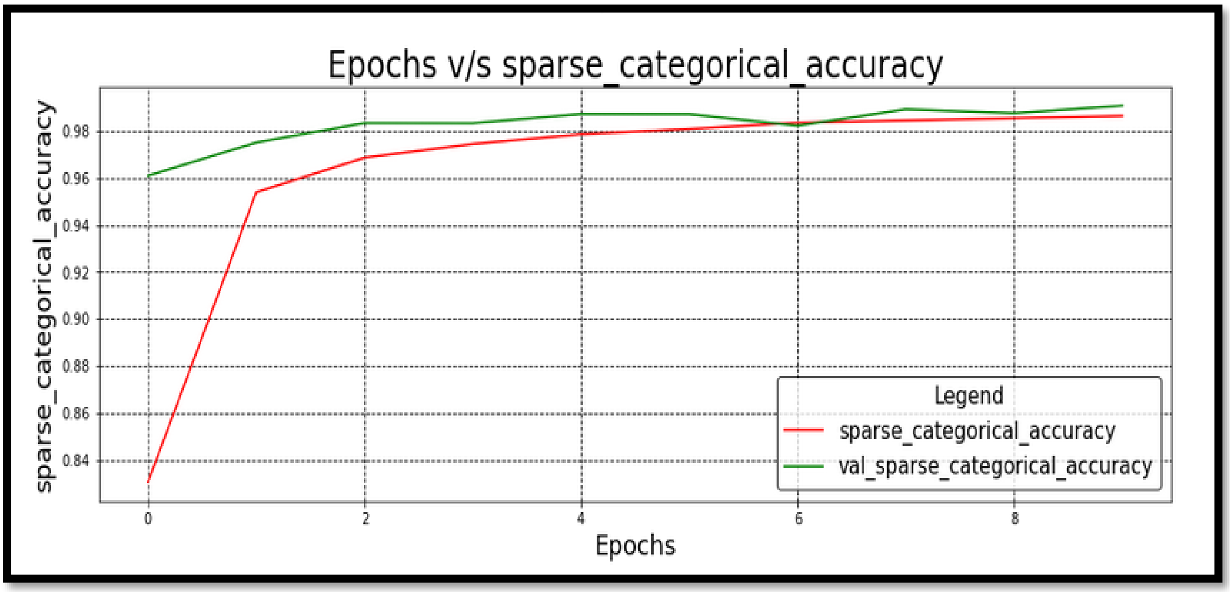


Figure 6. Accuracy at different epochs.

5. Results

5.1 Prediction

The saved model was loaded and used to predict mode condition of the Compressor. A function was written, where it prints the prediction class and its respective accuracy of the prediction.

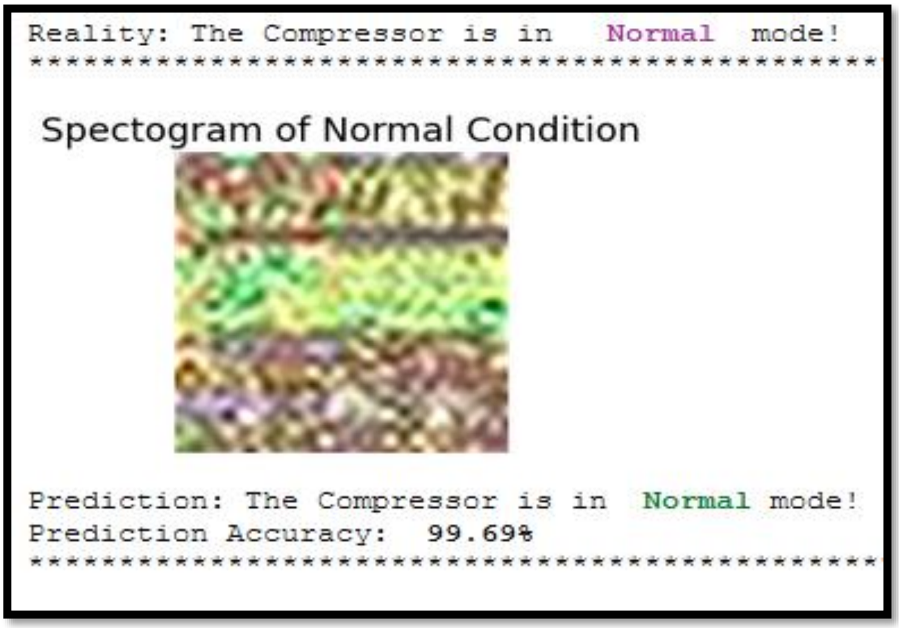


Figure 7. Prediction of Normal Class.

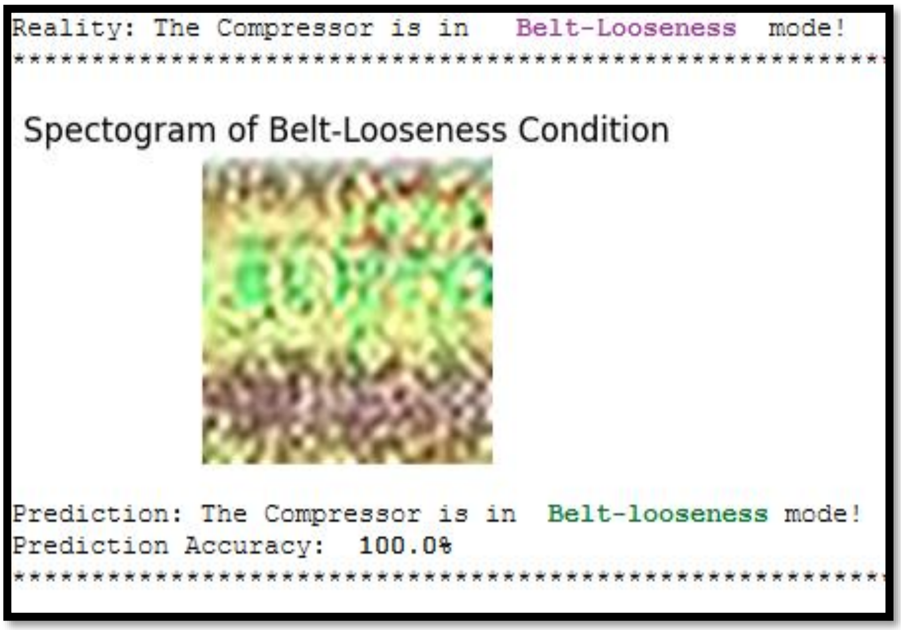


Figure 8. Prediction of Belt-Looseness Class.

Figure 9. Prediction of Belt-Looseness-High Class

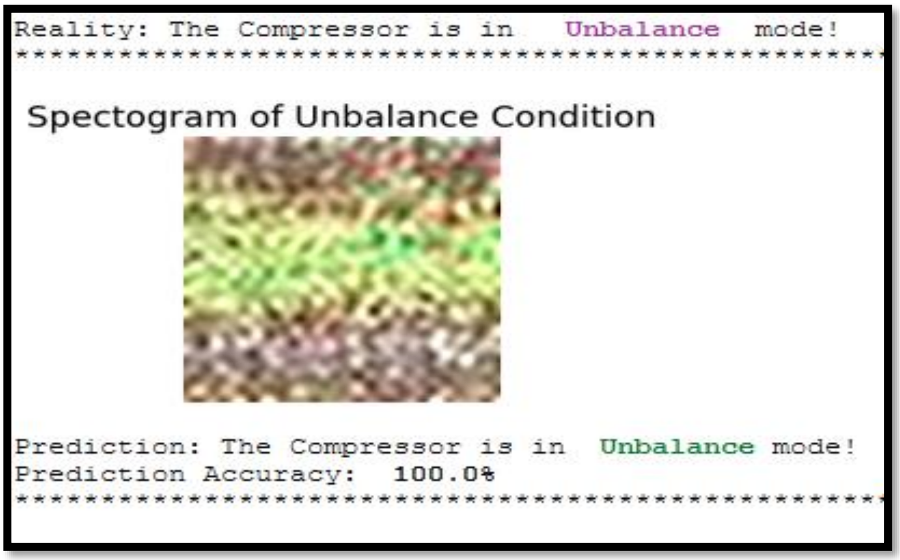


Figure 10. Prediction of Unbalance Class.

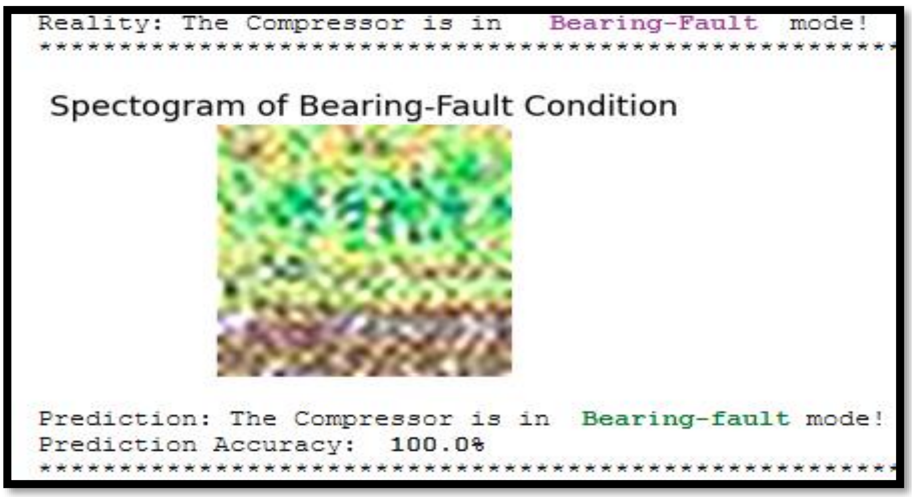


Figure 11. Prediction of Bearing-Fault Mode.

5.2 Confusion Matrix and Classification Report

The confusion matrix gives us an idea about how the model classified the spectrograms. Most of the images were correctly classified, though there is a high anomaly in the spectrograms of “Belt-Looseness-High” class as many images were classified as “Belt-Looseness class”.

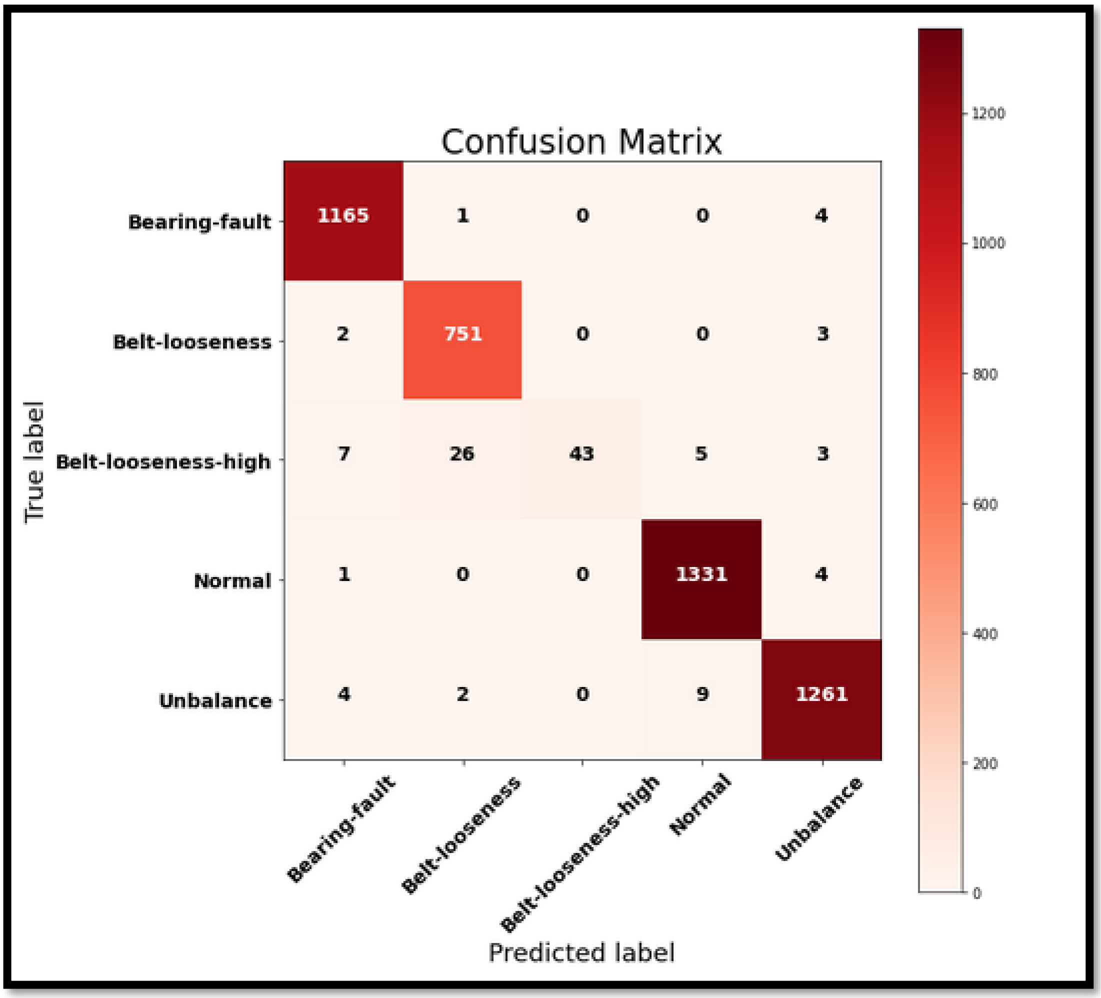


Figure 12. Confusion Matrix

Classification Report	precision	recall	f1-score	support
Bearing-Fault	0.99	1.00	0.99	1170
Belt-Looseness	0.96	0.99	0.98	756
Belt-Looseness-High	1.00	0.51	0.68	84
Normal	0.99	1.00	0.99	1336
Unbalance	0.99	0.99	0.99	1276
accuracy			0.98	4622
macro avg	0.99	0.90	0.93	4622
weighted avg	0.98	0.98	0.98	4622

Figure 13. Classification report giving details about Precision and Recall.

6. Conclusion

Short Time Fourier Transform Spectrograms can be successfully used to classify fault modes in a Screw Compressor.

In this project, the training accuracy was about 98%, validation accuracy was about 99% and the test accuracy was about 98.5%. The Confusion Matrix shows how many images were classified accurately and how many were falsely classified. The Classification report gives us the precision-recall- f1-score details.

Since, there was high anomaly in the “Belt-Looseness-High” class, maybe this class can be merged with “Belt-Looseness” class, further reducing the total number of classes to just four.

7. Reference

1. PHM Asia-Pacific 2021 Data Challenge: http://phmap.org/data-challenge/

2. Data: The data link from PHM 2021 Asia-pacific Website is given below. https://drive.google.com/drive/folders/1Zcth6UhPfP3vM8YadHhCSmK6v4aEyOA7