CHAPTER 3

Single-Fault Diagnosis of Self-Priming Centrifugal Pump

3.1 Introduction

Centrifugal pumps are very vital and abundantly used rotating machinery. Under an abnormal state, all rotating machinery are accompanied by changes in vibration. Vibration signal analysis has been in application for fault diagnosis of rotating machinery. Feature extraction is a vital stage that determines diagnosis accuracy, and substantial research has taken place on different types of feature extraction methods. In many techniques, a pre-decomposition of raw signal is also applied before the feature extraction. The most important components which succumb to failure in centrifugal pumps are the bearing and impeller. Therefore, the whole diagnosis in this research work is focused on pump-system failure due to failure of these components.

The operating state of bearing significantly affects the accuracy, reliability, and useful life of the pump-system.

The performance of knowledge-based methods relies on training data and quality of selected features heavily. In several studies, different feature extraction methods are proposed. The extracted features are given to classifiers as inputs.

CNN's are feed-forward and constrained 2D neural networks that have both alternating convolution and sub-sampling layers. Convolution layers model the cells in the human visual cortex [296]. CNN's have accomplished state-of-the-art performance. The Detection of faults in machines using an ANN based approach is proposed in [230],[233],[242].

3.2 Precision-Recall Metric to Evaluate Classifier Performance

Precision-Recall is a useful measure of success of prediction when the classes are very imbalanced. In information retrieval, precision is a measure of result relevancy, while recall is a measure of how many truly relevant results are returned.

True Positives (T_{P}): These are the correctly predicted positive values, which means that the value of the actual class is yes and the value of the predicted class is also yes. E.g., if actual class value indicates that this passenger survived and predicted class tells you the same thing.

True Negatives (T_{N}) These are the correctly predicted negative values, which means that the value of the actual class is no and the value of the predicted class is also no. E.g., if the actual class says this passenger did not survive and predicted class tells you the same thing.

False Positives (F_{P}): When actual class is no and predicted class is yes. E.g., if the actual class says this passenger did not survive but predicted class tells you that this passenger will survive.

False Negatives (F_{N}): When actual class is yes but predicted class in no. E.g., if actual class value indicates that this passenger survived and predicted class tells you that passenger will die.

Precision: Precision is the ratio of correctly predicted positive observations of the total predicted positive observations. The question that this metric answer is of all passengers that labelled as survived, how many survived? High precision relates to the low false positive rate. We have got 0.788 precision, which is pretty good.

$$Precision(P) = T_P / (T_P + F_P) \tag{3.1}$$

Recall (Sensitivity): Recall is the ratio of correctly predicted positive observations to all observations in actual class - yes. The question recall answers are: Of all the passengers that truly survived, how many did we label? We have got a recall of 0.631, which is good for this model as its above 0.5.

$$Recall(R) = T_P / (T_P + F_N) \tag{3.2}$$

F1 score: F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it’s better to look at both Precision and Recall.

$$F1Score = 2 * P * R / (P + R) \tag{3.3}$$

Accuracy: Accuracy is the most intuitive performance measure, and it is simply a ratio of correctly predicted observation to the total observations. One may think that if we have high accuracy, then our model is best. Yes, accuracy is a great measure but only when you have symmetric datasets where values of false positive and false negatives are almost the same. Therefore, you have to look at other parameters to evaluate the performance of your model. For our model, we have got 0.803, which means our model is approx. 80% accurate.

$$Accuracy = (T_P + T_N)/ (T_P + F_P + T_N + F_N) \tag{3.4}$$

The precision-recall curve: The precision-recall curve shows the trade-off between precision and recall for different threshold. A high area under the curve represents both high recall and high precision, where high precision relates to a low false positive rate, and high recall relates to a low false negative rate. High scores for both show that the classifier is returning accurate results (high precision), as well as returning a majority of all positive results (high recall) The relationship between recall and precision can be observed in the stairstep area of the plot. At the edges of these steps, a small change in the threshold considerably reduces precision, with only a minor gain in the recall.

Precision-recall curves are typically used in binary classification to study the output of a classifier. To extend the precision-recall curve and average precision to multiclass or multi-label classification, it is necessary to binarize the output. One curve can be drawn per label, but one can also draw a precision-recall curve by considering each element of the label indicator matrix as a binary prediction (micro-averaging).

3.3 The Basic Theory of CNN and Proposed Method

Then the input to a convolutional layer is a m x n x r image where r is the number of multimedia channels, which for RGB image has r=3. The convolutional layer will have k filters (or kernels) of size m x n x q, where n is smaller than the dimension of the image (m) and q can either be the same as the number of channels r or smaller and may vary for each kernel. Each map is then sub-sampled typically max pooling over p x p regions with p ranges between 2 to 5 for smaller and larger inputs respectively. The figure below illustrates a full layer in a CNN consisting of convolutional and sub-sampling sub-layers

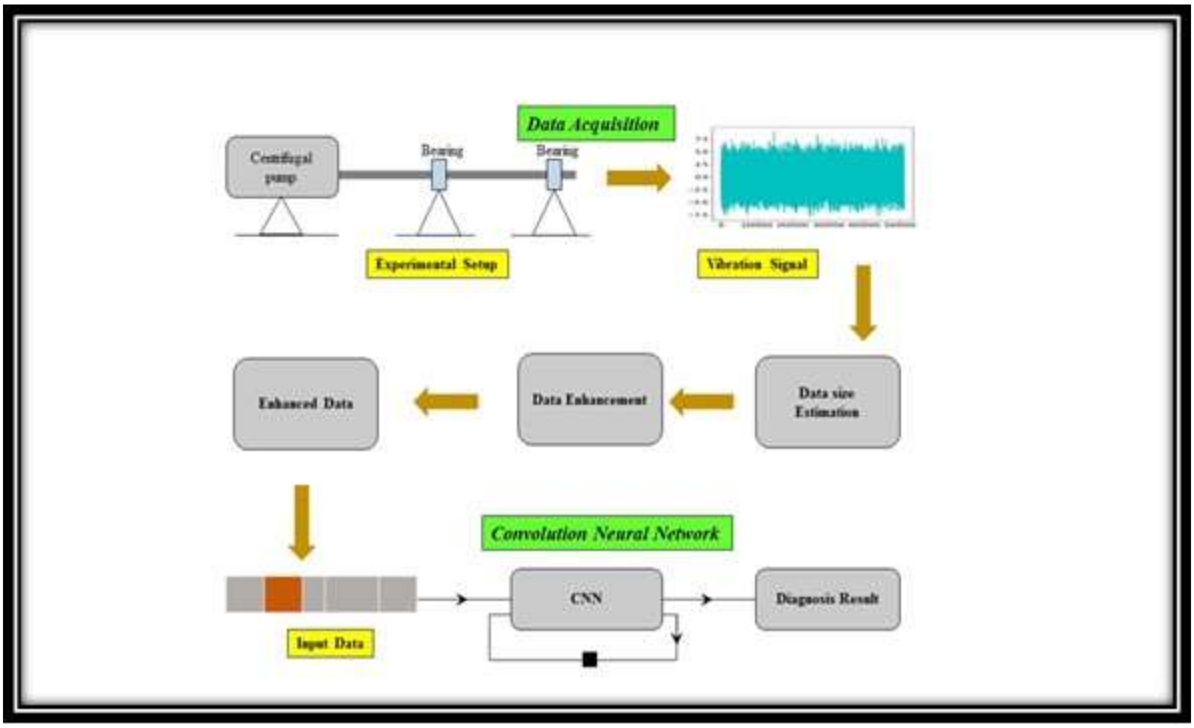


Figure 3.1: Flow chart of Proposed Method

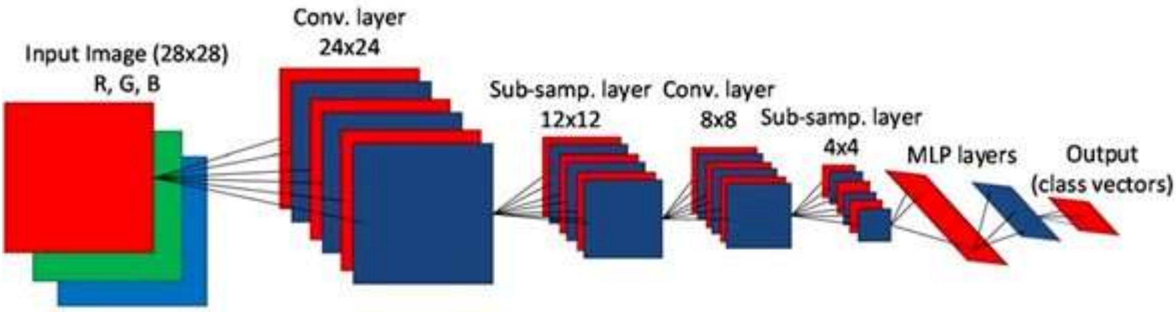


Figure 3.2: 2D CNN configuration

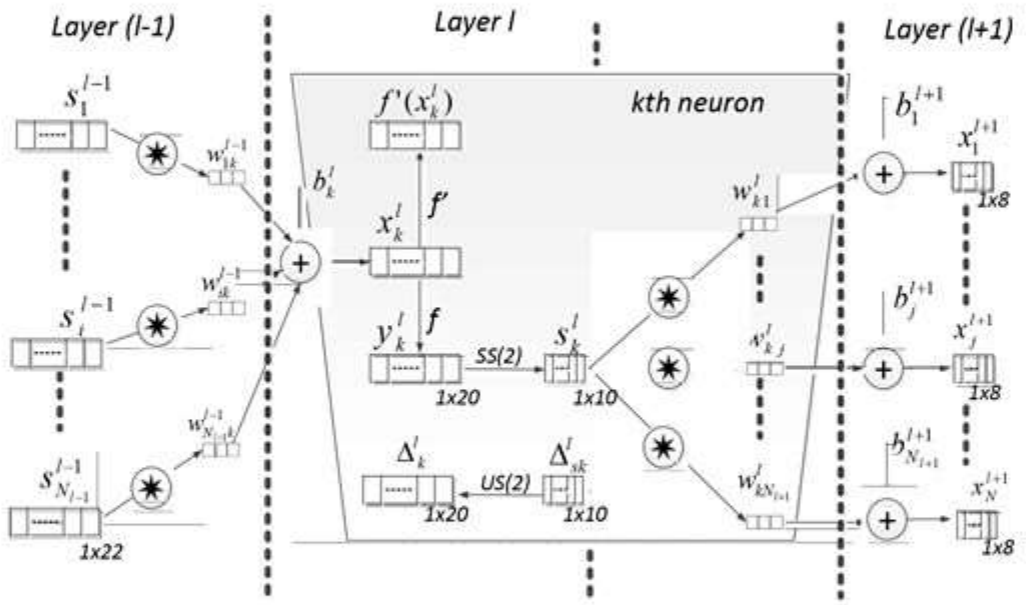


Figure 3.3: The convolution layers of the 1D CNN configuration

3.4 Data Description

The data of self-priming centrifugal pump are collected on a self-priming centrifugal pump data acquisition system, as shown in Fig 3.5. The acceleration sensor is installed above the motor housing, and the sensor is fixed on a specific pedestal. According to the requirement of fault diagnosis for centrifugal pump, a data acquisition experimental scheme is created for the fault insertion test. The test covers primarily fault modes. The experiment items are listed in Table 3.1. In the experiment, the rotation speed is 2,900 RPM. An acceleration sensor is employed when sampling. The sample frequency is 10239Hz. Vibration data are collected under normal conditions and fault conditions, including bearing roller wearing, inner race wearing, and outer race wearing fault conditions, as well as impeller wearing fault condition. The sampling time is 2s for each set, and one set is collected every 5 seconds. The centrifugal pump data used here are provided by the PloS One [162]

Table 3.1: Description of the centrifugal pump data set

Test object	**Failure test**	**Normal test**
Rolling bearings	Bearing inner race wearing test	Bearing normal operation test
	Bearing outer race wearing test	
	Bearing rollers wearing test	
Impeller	Impeller wearing test	

Table 3.2: Data-set size for different fault classes

Class (0)	**Sample no**	**Data Points**		
	sample1	data1	—	data 1024
	sample2		—	data 1024
Bearing	—	data1		
normal	sample100		—	data 1024
Class (1)				
	sample1	data1	—	data 1024
	sample2	data1	—	data 1024
outer race	—			
	sample100	data1	—	data 1024
Class (2)				
	sample1	data1	—	data 1024
inner race	sample2	data 1	—	data 1024
	—			
	sample100	data1	—	data 1024
Class (4)				
rollers	sample1	data1	—	data 1024
	sample2	data1	—	data 1024
	—			
	sample100	data1	—	data 1024
Class (5)				
impeller	sample1	data1	—	data 1024
	sample2	data1	—	data 1024
	—			
	sample100	data1	—	data 1024

Table 3.3: Description of Fault levels used for centrifugal pump data-set

Fault type	Bearing normal	outer race	inner race	rollers	impeller
Level	0	1	2	3	4

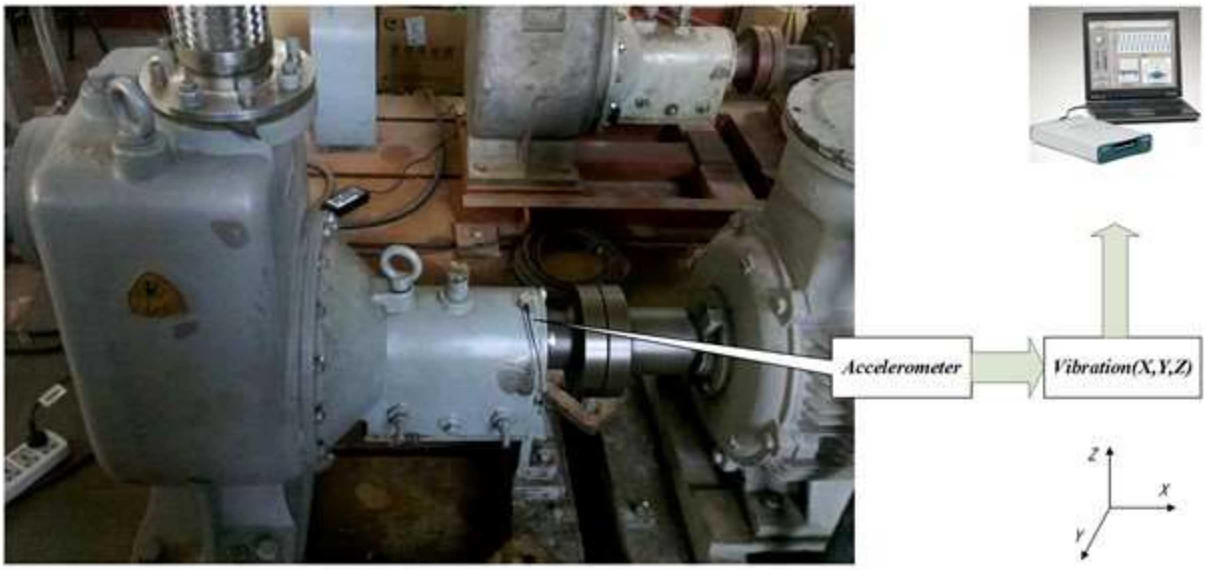


Figure 3.4: The experiment set-up

Table 3.4: Data static after data enhancement remains unchanged.

Data Enhancement	Training time	Kurtosis	Skewness	Variance
100 percent Data	120.06	3.7165	0.01601	201261.90
200 percent Data	100.04	3.7165	0.01601	201261.90
300 percent Data	96.4	3.7165	0.01601	201261.90
400 percent Data	79.91	3.7165	0.01601	201261.90

3.5 Results and Analysis

We have tested the effectiveness of CNN-2D, CNN-1D, and ANN methods for Fault Diagnosis using for fault classification. We see from table 3.3 and figure-3.8 that the Computation time falls drastically as we enhanced the data more and more. We also notice that the central moments like variance, skewness, and kurtosis remain unaltered due to data enhancement, which ensures that basic properties of data remain the same due to such type of enhancement.

Table 3.5: Performance of ANN with different levels of data enhancement

ANN (100 percent Data)

Class	precision	recall	f1-score	support
0	0.14	0.11	0.12	18
1	0.07	0.18	0.11	11
2	0.3	0.29	0.29	28
3	0.29	0.28	0.29	18
4	0.2	0.12	0.15	25
Avg/tot	0.22	0.2	0.2	100

Testing accuracy =20.0percent

Training accuracy =21.95 percent

ANN (200 percent Data)

Class	precision	recall	f1-score	support
0	0.84	0.72	0.78	36
1	0.69	0.82	0.75	33
2	0.74	0.89	0.8	44
3	0.82	0.82	0.82	39
4	0.84	0.67	0.74	48
Avg/tot	0.79	0.78	0.78	200

Testing accuracy =78.00percent

Training accuracy=80.98 percent

ANN (300 percent Data)

Class	precision	recall	f1-score	support
0	0.96	0.87	0.91	60
1	0.81	0.96	0.88	56
2	0.93	0.93	0.93	58
3	0.9	0.91	0.9	67
4	0.94	0.85	0.89	59
Avg/tot	0.91	0.9	0.9	300

Testing accuracy =90.33 percent

Training accuracy=94.63 percent

ANN (400 percent Data)

Class	precision	recall	f1-score	support
0	0.96	0.99	0.98	82
1	0.96	1	0.98	68
2	0.99	1	0.99	83
3	1	0.97	0.98	96
4	1	0.96	0.98	71
Avg/tot	0.98	0.98	0.98	400

Testing accuracy =98.25 percent

Training accuracy =98.45 percent

ANN (500 percent Data)

Class	precision	recall	f1-score	support
0	1	0.97	0.98	93
1	1	1	1	95
2	0.97	1	0.99	105
3	1	1	1	102
4	1	1	1	105
Avg/tot	0.99	0.99	0.99	500

Testing accuracy =99.40 percent

Training accuracy =99.50 percent

ANN (600 percent Data)

Class	precision	recall	f1-score	support
0	0.97	1	0.99	110
1	1	1	1	120
2	1	0.98	0.99	132
3	1	1	1	121
4	1	1	1	117
Avg/tot	1	0.99	1	600

Testing accuracy=99.50 percent

Training accuracy =99.37 percent

Table 3.6: Performance of Logistic Regression with different levels of data enhancement

Logistic Regression(100percentData)

Class	precision	recall	f1-score	support
0	0.27	0.33	0.3	18
1	0.12	0.36	0.19	11
2	0.27	0.14	0.19	28
3	0.18	0.17	0.17	18
4	0.07	0.04	0.05	25
Avg/tot	0.19	0.18	0.17	100

Testing accuracy = 18percent
Training accuracy =19.5percent

Logistic Regression (200percentData)

Class	precision	recall	f1-score	support
0	0.79	0.83	0.81	36
1	0.78	0.88	0.83	33
2	0.91	0.91	0.91	44
3	0.95	0.9	0.92	39
4	0.91	0.83	0.87	48
Avg/tot	0.87	0.87	0.87	200

Testing accuracy =87percent
Training accuracy =78.5percent

Logistic Regression (300percentData)

Class	precision	recall	f1-score	support
0	0.95	1	0.98	60
1	0.95	1	0.97	56
2	0.95	0.95	0.95	58
3	1	0.91	0.95	67
4	1	1	1	59
Avg/tot	0.97	0.97	0.97	300

Testing accuracy =97percent
Training accuracy =94.7percent

Logistic Regression (400percentData)

Class	precision	recall	f1-score	support
0	1	1	1	82
1	1	1	1	68
2	1	1	1	83
3	1	1	1	96
4	1	1	1	71
Avg/tot	1	1	1	400

Testing accuracy =100percent
Training accuracy =98.4percent

Logistic Regression (500percentData)

Class	precision	recall	f1-score	support
0	1	1	1	93
1	1	1	1	95
2	1	1	1	105
3	1	1	1	102
4	1	1	1	105
Avg/tot	1	1	1	500

Testing accuracy =100percent
Training accuracy =99.8percent

Logistic Regression (600percentData)

Class	precision	recall	f1-score	support
0	1	1	1	110
1	1	1	1	120
2	1	1	1	132
3	1	1	1	121
4	1	1	1	117
Avg/tot	1	1	1	600

Testing accuracy =100percent
Training accuracy =99.8percent

Table 3.7: Performance of 1-D CNN with different levels of data enhancement

1D-CNN (100percentData)

Class	precision	recall	f1-score	support
0	0.11	0.11	0.11	18
1	0.17	0.18	0.17	11
2	0.5	0.32	0.39	28
3	0.24	0.44	0.31	18
4	0.22	0.16	0.19	25
Avg/tot	0.28	0.25	0.25	100

Testing accuracy = 25percent
Training accuracy =19.5percent

1D-CNN (200percentData)

Class	precision	recall	f1-score	support
0	0.82	0.78	0.8	36
1	0.72	0.79	0.75	33
2	0.85	0.8	0.82	44
3	0.78	0.79	0.78	39
4	0.76	0.77	0.76	48
Avg/tot	0.79	0.79	0.79	200

Testing accuracy =78.5percent
Training accuracy =73.6percent

1D-CNN (300percentData)

Class	precision	recall	f1-score	support
0	0.96	0.88	0.92	60
1	0.93	0.95	0.94	56
2	0.83	0.98	0.9	58
3	0.92	0.9	0.91	67
4	0.87	0.8	0.83	59
Avg/tot	0.9	0.9	0.9	300

Testing accuracy =90percent
Training accuracy =93percent

1D-CNN (400percentData)

Class	precision	recall	f1-score	support
0	1	1	1	82
1	0.96	1	0.98	68
2	1	1	1	83
3	1	1	1	96
4	1	0.96	0.98	71
Avg/tot	0.99	0.99	0.99	400

Testing accuracy = 99.25percent
Training accuracy =98.45percent

1D-CNN (500percentData)

Class	precision	recall	f1-score	support
0	1	0.97	0.98	93
1	1	1	1	95
2	1	1	1	105
3	0.97	1	0.99	102
4	1	1	1	105
Avg/tot	0.99	0.99	0.99	500

Testing accuracy =99.40percent
Training accuracy =99.5percent

1D-CNN (600percentData)

Class	precision	recall	f1-score	support
0	1	1	1	110
1	1	1	1	120
2	1	1	1	132
3	1	1	1	121
4	1	1	1	117
Avg/tot	1	1	1	600

Testing accuracy =100percent
Training accuracy =100percent

Table 3.8: Performance of 2-D CNN with different levels of data enhancement

2D-CNN (100percentData)

Class	precision	recall	f1-score	support
0	0.36	0.5	0.42	18
1	0.15	0.36	0.21	11
2	0	0	0	28
3	0.15	0.11	0.13	18
4	0.17	0.16	0.17	25
Avg/tot	0.15	0.19	0.16	100

Testing accuracy = 19.0percent
Training accuracy =19.5percent

2D-CNN (200percentData)

Class	precision	recall	f1-score	support
0	0.74	0.81	0.77	36
1	0.8	0.85	0.82	33
2	0.77	0.84	0.8	44
3	0.86	0.82	0.84	39
4	0.83	0.71	0.76	48
Avg/tot	0.8	0.8	0.8	200

Testing accuracy =80.0percent
Training accuracy =76.7percent

2D-CNN (300percentData)

Class	precision	recall	f1-score	support
0	1	0.9	0.95	60
1	0.96	0.98	0.97	56
2	0.86	0.93	0.89	58
3	0.91	0.9	0.9	67
4	0.83	0.85	0.84	59
Avg/tot	0.91	0.91	0.91	300

Testing accuracy =91.0percent
Training accuracy =93.38percent

2D-CNN (400percentData)

Class	precision	recall	f1-score	support
0	1	1	1	82
1	1	1	1	68
2	0.97	1	0.98	83
3	0.97	0.97	0.97	96
4	1	0.96	0.98	71
Avg/tot	0.99	0.98	0.98	400

Testing accuracy =98.5
Training accuracy =98.14

2D-CNN (500percentData)

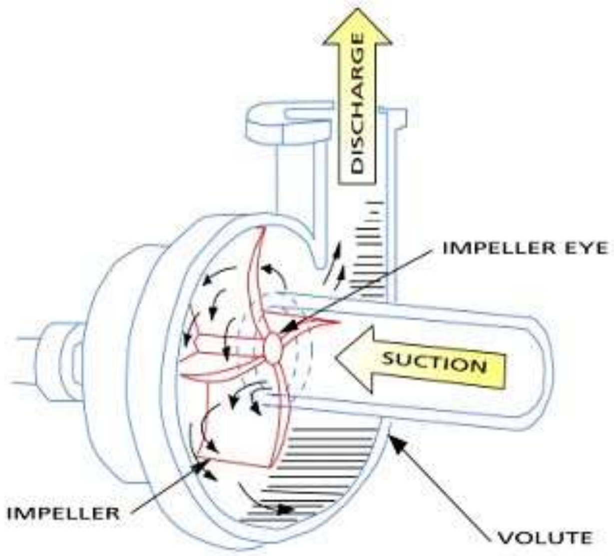
Class	precision	recall	f1-score	support
0	1	0.97	0.98	93
1	0.97	1	0.98	95
2	1	1	1	105
3	1	1	1	102
4	1	1	1	105
Avg/tot	0.99	0.99	0.99	500

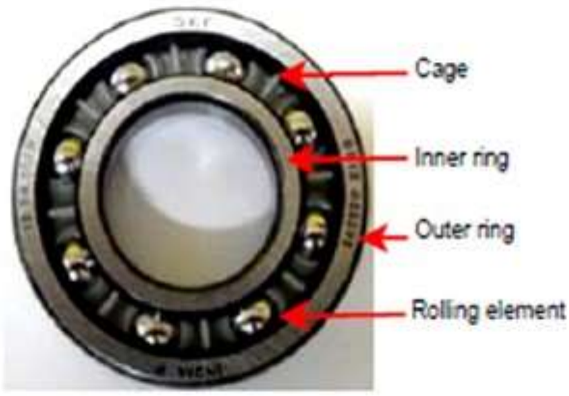
Testing accuracy =99.2percent
Training accuracy =99.5percent

2D-CNN (600percentData)

Class	precision	recall	f1-score	support
0	0.97	1	0.99	110
1	1	1	1	120
2	1	0.98	0.99	132
3	1	1	1	121
4	1	1	1	117
Avg/tot	1	0.99	1	600

Testing accuracy =99.4percent
Training accuracy =99.5percent





Bearing

Figure 3.5: The impeller and bearing of centrifugal pump

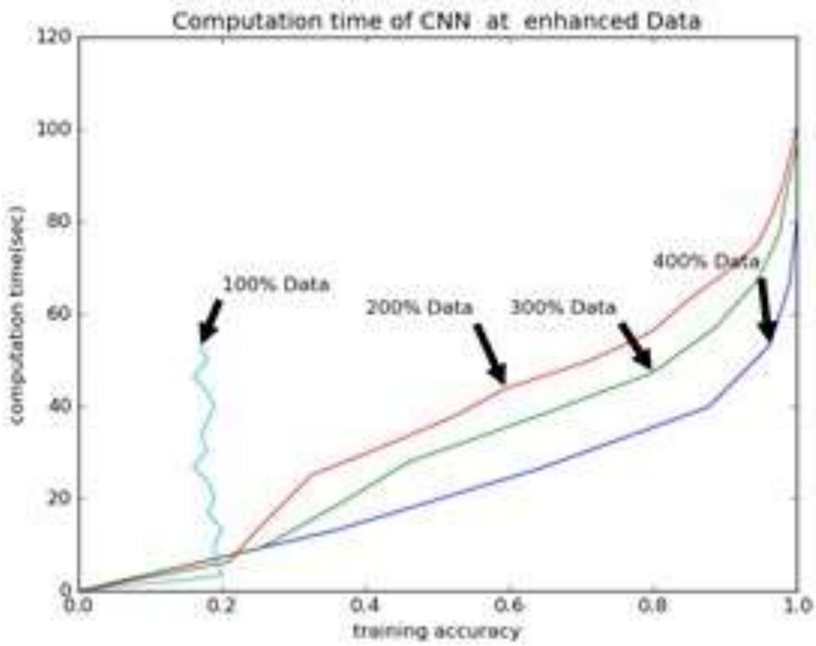


Figure 3.6: The Epochs vs. Training accuracy of CNN

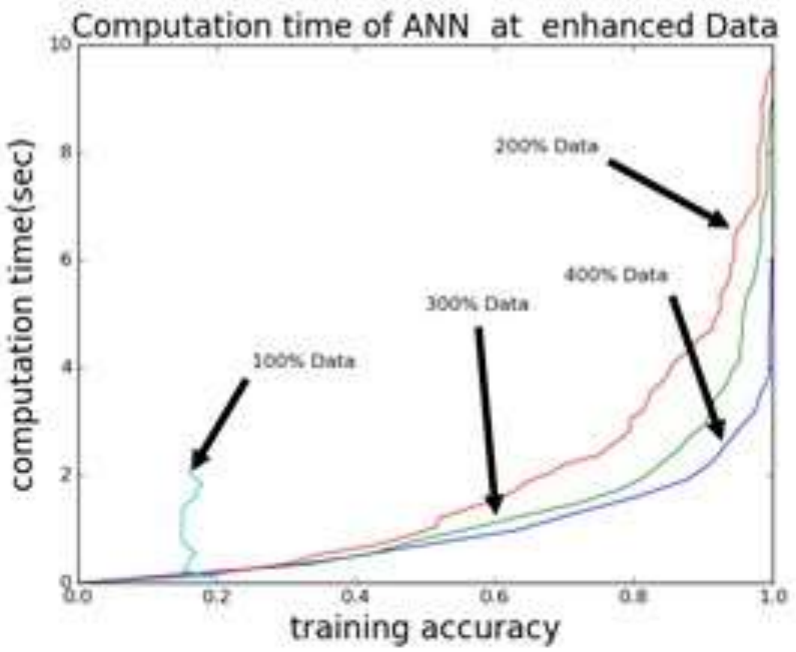


Figure 3.7: The Epochs vs. Training accuracy of ANN

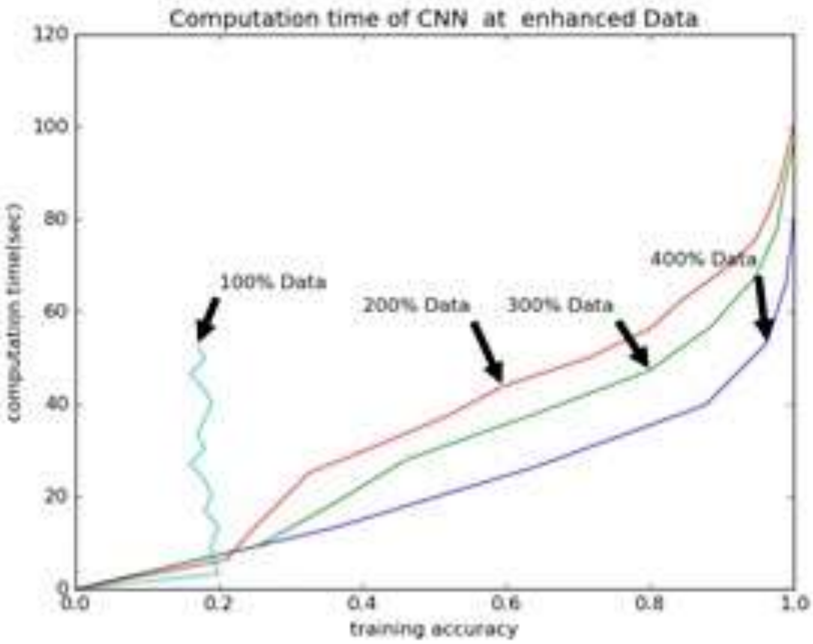


Figure 3.8: CNN-2D performance after different amount of data enhancements.

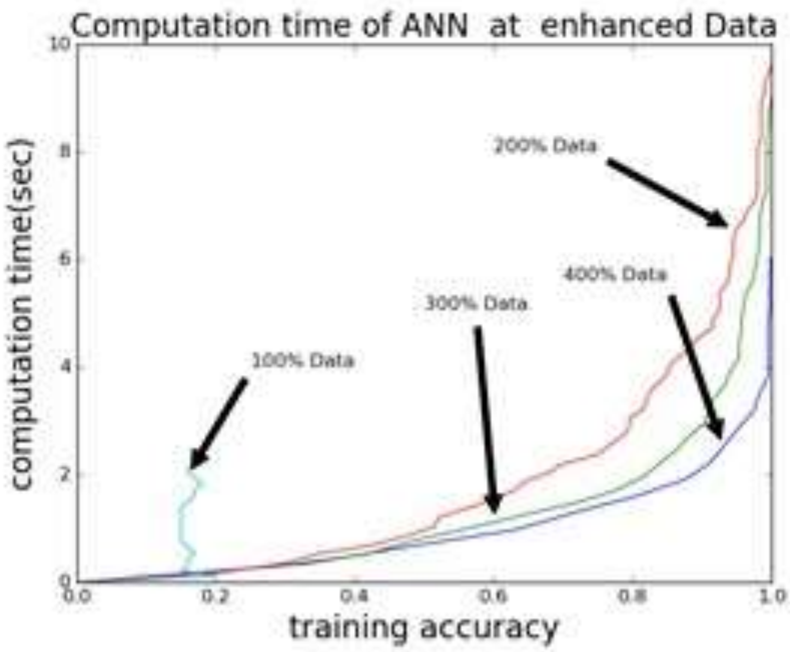
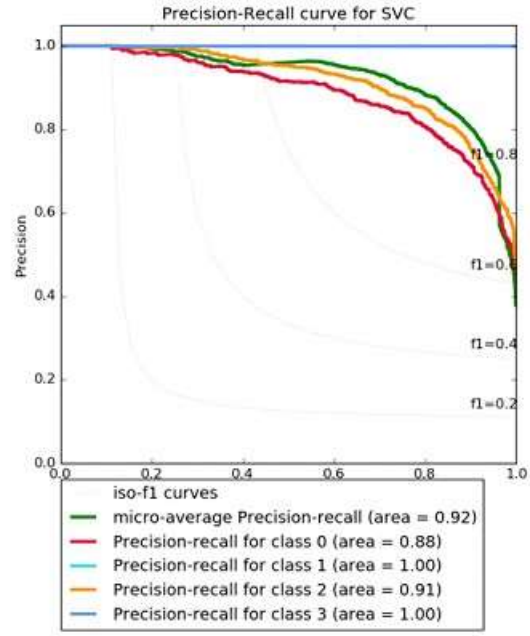
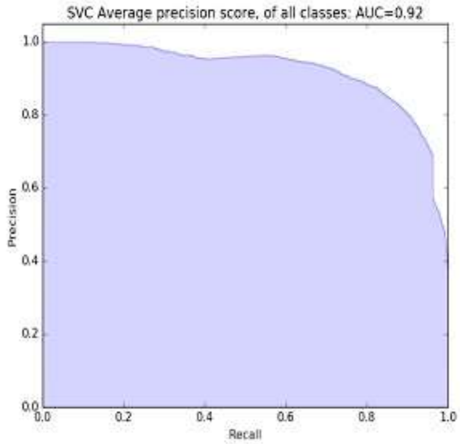
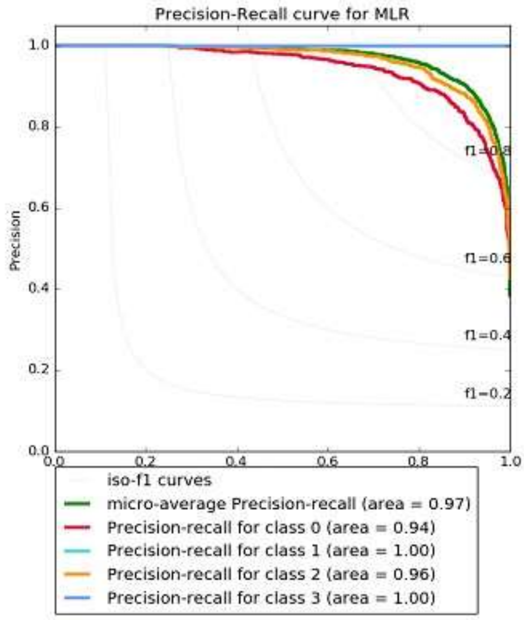


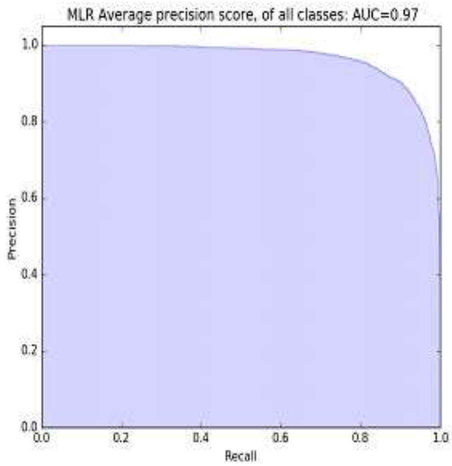
Figure 3.9: ANN performance after different amount of data enhancements.





Data enhancement = 400%





Data enhancement = 400%

Figure 3.10: Precision-Recall curves for SVC and MLR for centrifugal pump

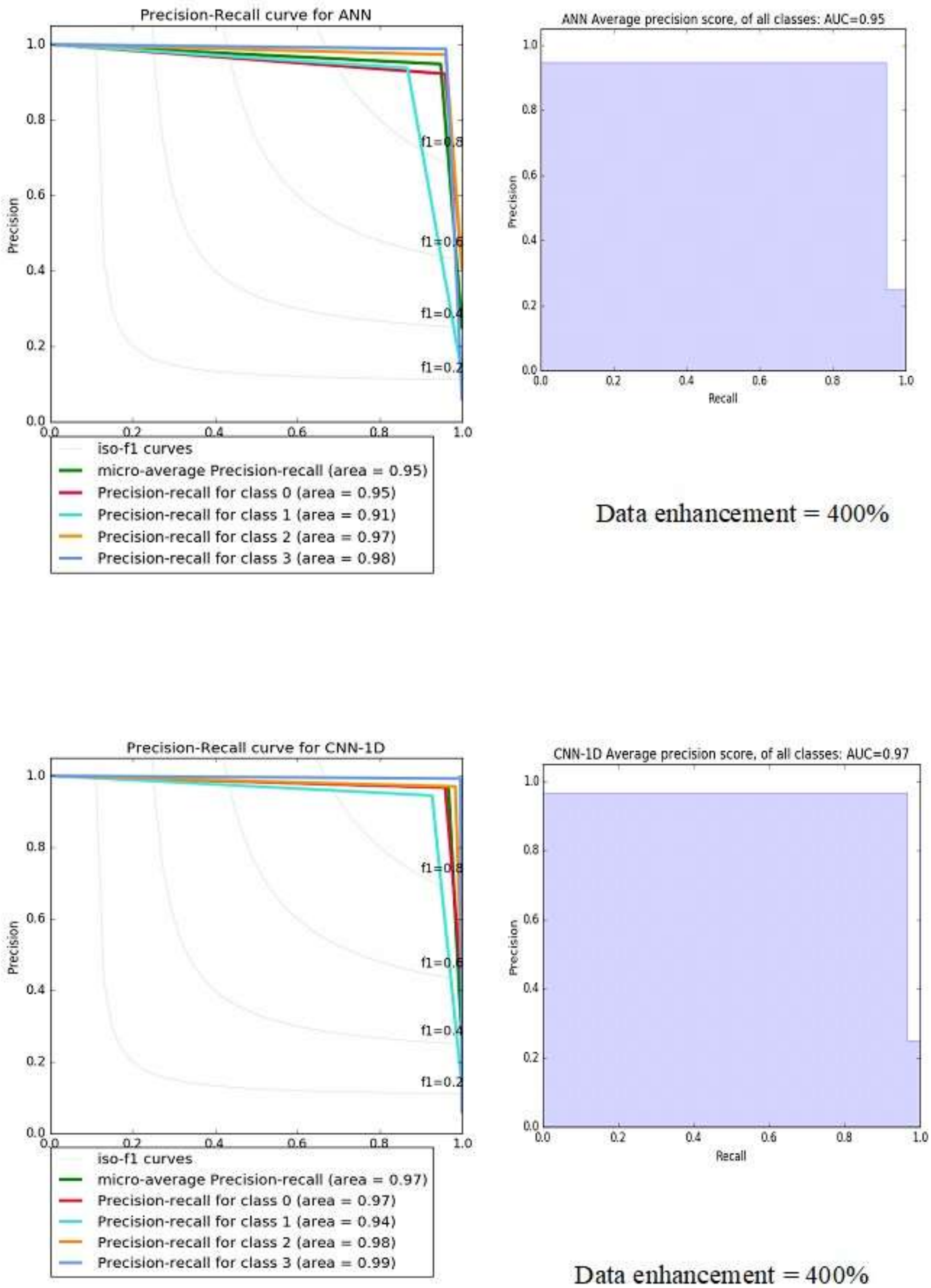


Figure 3.11: Precision-Recall curves for ANN and CNN-1D for centrifugal pump

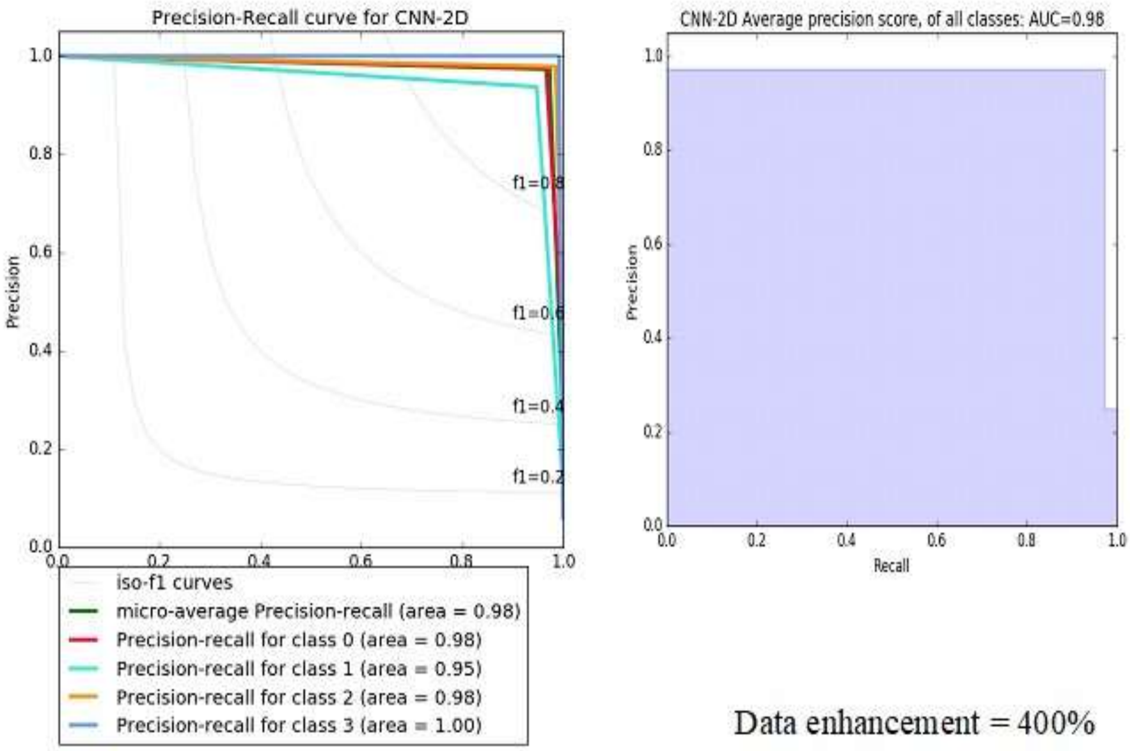


Figure 3.12: Precision-Recall curves for CNN-2D for centrifugal pump

3.6 Conclusion

CNN is very powerful deep learning technique for classification when the size of data is significant. It is observed that it fails to give any reasonable classification when the size of data is small. This chapter deals with enhanced data technique, which is very useful for the smaller size of available data. It is proposed to increase the size of data to multiple times until a good classification accuracy is acquired. The chapter shows that the neural networks perform very efficiently when such type of enhancement is done. It has been elaborated for evaluating the classification of faults of centrifugal pumps. The CNN-2D and CNN-1D yield 100% accuracy for diagnosing the faults in this case. The performance is also compared with that of ANN. The number of epochs required to reach 100% accuracy for different multiple sizes of data is used to evaluate the performance. The enhanced data approach also shows that there is a drastic fall in overall classification time of CNN.