CHAPTER 6

Conclusions and Scope for Future Work

6.1 Conclusions

This thesis provides several significant contributions to the analysis and modelling of machine learning-based data-driven methods which lay the foundations for the solution of structural health monitoring problems. Here we highlight the most significant aspects of these contributions.

We presented the application of machine learning methods for early prediction of the failures of self- priming centrifugal pumps with the help of methods like Support Vector Classification, Multinomial Logical Regression, Artificial Neural Networks and especially, Convolution Neural Networks. A persistent problem of machine learning methods is that they there are not much successful for the cases where the data size is small. The thesis presented a smart data enhancement technique for such cases, which proves its effect by providing better classification results in all machine learning algorithms.

We presented method to apply deep-learning for the structural health monitoring of mechanical systems. We succeeded in our task in identifying the early failures of bearings due to the cracks developed on small rollers, originated under complicated" spin" and" revolution" motion, which were earlier found to be very difficult be identified. We presented a method based on the smart decomposition of signals with the help of Ensembled Empirical Mode Decomposition technique, which has the capability of spurious denoising signals contained in the raw vibration data. The filtered and decomposed signals were again merged into a high-frequency signal, and low-frequency signal groups called CMFs.

It exhibits that different frequencies emitted by the bearing could be grouped separately. We exploited the knowledge of deep learning for feature selection and classification. The methods like CNN can automatically extract features and, subsequently, classify the data precisely. The combined approach resulted in a very successful bearing fault detection at early stages, particularly when the faults are very fine. The deep learning methods do not require any feature selection. This is inbuilt in the algorithms of deep neural networks. Hence a lot of time is saved. The early detection and diagnosis of fault on rotating machines by machines learning assisted data-driven methods can be very easily used and very precisely processed; the real-time solutions are possible with the extension of this combined approach.

In this research work, we have addressed the problem of estimation of remaining useful life successfully, as an important part of prognostics. A new method based on stacked gradient boosted trees has been explored and implemented successfully. This method outperforms the other contemporary techniques like Support Vector Regression, CNN, Gradient Boosted Trees for smallest square mean errors. Its capability of predicting the remaining useful life fault detection is shown. This technique is validated on an open resource data of C-MAPSS.

The accuracy, reliability, and computational cost are crucial issues in any efficient method. The machine learning methods require the least time and least number of iterations to complete the process of detection of a fault. Hence, they are better to the contemporary methods, as far as cost- effectiveness is concerned.

6.2 Scope for Future Work

This research work provides several opportunities for continuing research in the area of machine learning based on structural health monitoring. We development and demonstrated the validity of several fault diagnosis and prognosis methods of structural health monitoring problem. The real-time solutions based on machine learning are the future works in this area. The internet of things (IOT) based data management system at a large number of places might provide a bigger data for continuous fault detection and diagnosis.

A big challenge in data-driven methods is the noise, because they are generated with every motion, a component performs. There are challenges regarding efficient filters in signal processing, to completely denoise the data generated at the real operational time, particularly, in the cases of bearing, where frequencies for each type of crack occurred simultaneously. If smart filters are developed, this problem of fault diagnosis will be easily be solved. Hence, there is a need to develop smart noise filters in future research work. Along with these filters, machine learning methods will become more efficient.