

# Automated Valve Fault Detection Based on Acoustic Emission Parameters and Artificial Neural Network

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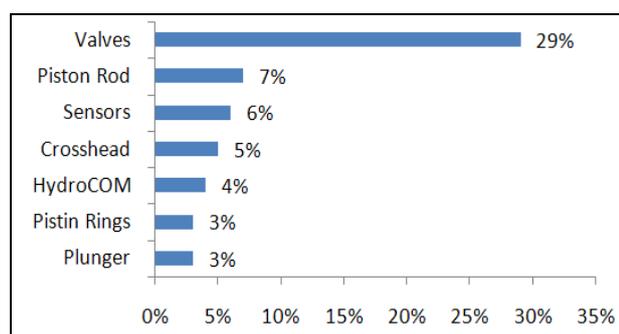
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**Abstract.** Reciprocating compressor is one of the most popular classes of machines use with wide applications in the industry. However, valve failures in this machine often results unplanned shutdown. Therefore, the effective valve fault detection technique is very necessary to ensure safe operation and to reduce the unplanned shutdown. This paper propose an artificial intelligence (AI) model to detect valve condition in reciprocating compressor based on acoustic emission (AE) parameters measurement and artificial neural network (ANN). A set of experiments were conducted on an industrial reciprocating air compressor with several operational conditions including good valve and faulty valve to acquire AE signal. A fault detection model was then developed from the combination of healthy-faulty data using ANN tool box available in MATLAB. The results of the model validation demonstrated accuracy of valves condition classification exceeding 97%. Eventually, the authors intend to do more efforts for programming this model in smart portable device which can be one of the innovative engineering technologies in the field of machinery condition monitoring in the near future.

## 1. Introduction

The valves consider a crucial component in any reciprocating compressor due to the valve essential role in compressor efficiency. Design optimization and development of the valves have been studied by many researchers [1-3]. Nevertheless, the valves still sited as the main reason of unplanned shutdown for the reciprocating compressor [4-6] as shows in Figure 1. Thus, valves condition monitoring is extremely important to reduce the unplanned shutdown.



**Fig. 1.** The main problems of the reciprocating compressors [5].

Various diagnosis methods have been investigated to diagnose valve faults in reciprocating compressors. PV diagram and support vector machines (SVM) have been used to detected and classify reciprocating compressor valves faults in several studies [7, 8]. Jing and Shijie [9] analyzed the torsional vibration of large scale compressors and identified failure can resulted from the exceeded vibration on compressor components. Van et al. [6] presented a new approach for valve fault diagnosis of reciprocating compressors valve using three signals including pressure, vibration and current of induction motor. They classify the valve fault using the deep belief networks (DBN). Elhaj et al. [10] used a numerical simulation and experimental study includes cylinder pressure waveforms and crankshaft instantaneous angular speed (IAS) to detect compressor valves faults features. Houxi et al. [11] employed the information entropy and support vector machine (SVM) method to for valve fault diagnosis in reciprocating compressors. Many studies illustrated that AE technique can detect the fault in the initial stage at lower speed while conventional vibration technique is not able [12-16].

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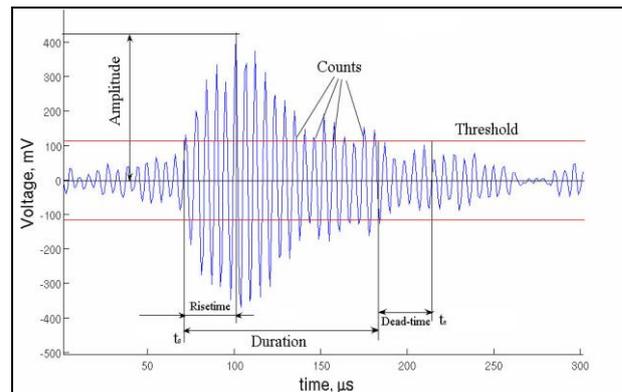
Several scholars investigated the viability of AE technique to detect valves fault in reciprocating compressors. For instant, Yuefei et al. [17] studied an integrating method using AE signal and simulated valve motion for valve faults diagnosis in reciprocating compressors. Alfayez et al. [18] investigated the AE application for cavitation detection in large scale centrifugal pump, they observed a clear relationship between AE RMS and the incipient cavitation. Sim et al [19] investigated the AE signal to identify the valve failure in reciprocating compressors. They use wavelet transform to decompose AE signal into different frequency ranges. Next, the RMS value was computed at each segment. Lastly, statistical analysis was performed to identify the best time–frequency segments can represent the valve condition. Although some of these methods were able to detect valve condition, but they are still not easy to employ in the industry. This paper proposes new methodology to develop a valve monitoring model based on AE signal parameters and ANN approach. The model can identify valve condition effectively and efficiently.

## 2. Theoretical Background

### 2.1. AE Signal Characteristic

According to American society for testing and materials (ASTM), AE refers to the generation of transient elastic waves produced by a rapid release of energy from localized source within the material; such as cracking, rubbing, impacting, cavitations, and leakage, with a typical operating frequency range beyond human hearing threshold of 100KHz to 1MHz [20, 21].

AE signal can be classified as transient signal when individual bursts (hits) clearly stray from background noises. While it can be a continuous signal if the signal has various amplitudes and frequencies along the time. When the form of AE signal has both transient and continuous it then called by a mix mode signal [22]. AE has special parameters which can be extracted from the AE acquired signal. The main AE parameters are illustrated in Figure 2 and Table 1.



**Fig. 2.** AE signal parameters

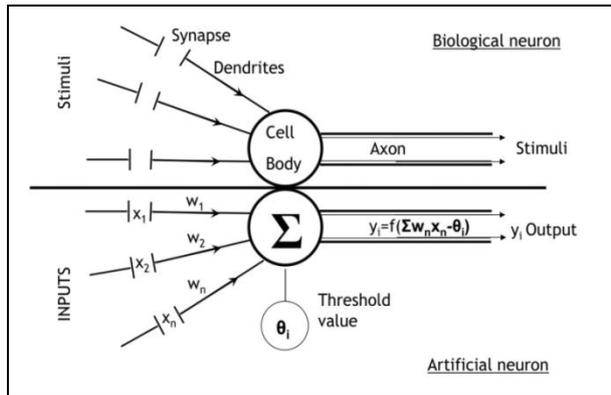
**Table 1.** Main AE signal parameters

AE Signal Parameters	Description	Units
Amplitude	The greatest measured voltage in a waveform.	Volt
Counts	The number of times the AE signal exceeds a preset threshold during an event.	Counts
Duration	The time between AE signal start and AE signal end.	μsec
Energy	The mean area under the rectified signal envelope.	MARSE
Absolute energy	The real amounts of AE signal energy.	Attojoule (aJ)
ASL	The average signal level of the AE amplitude.	db
Signal strength	The integral of the rectified voltage signal over the duration of the AE waveform packet	V.sec

In this paper, seven AE signal parameters will be use to develop the valve condition identification model. Multivariate analysis approach was used to nominate the most sensitive parameter to the compressor operational conditions by the author’s previous work [23-25] .

### 2.2. Artificial Neural Network

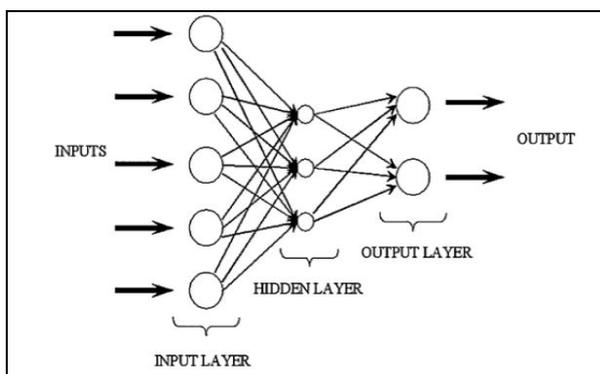
Artificial neural networks (ANNs) are a family of statistical learning models inspired by biological neural networks based on the neural structure of the brain. ANNs usually are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. ANNs are generally presented as systems of interconnected "neurons" which exchange messages between each other. The connections have numeric weights that can be tuned based on experience, making neural nets adaptive to inputs and capable of learning. Figure 3 show a simple comparison between a biological neuron and an artificial neuron.



**Fig. 3.** Biological neuron and artificial neuron.

The first fundamental modeling of neural networks was explained in 1943 by McCulloch and Pitts in terms of a computational model of nervous activity [26]. In recent years neural computing become a common used method in many fields because of their ability to measure nonlinear relationships in complex processes. Therefore, ANN have been employ in machine faults prediction and classification problems [27, 28]

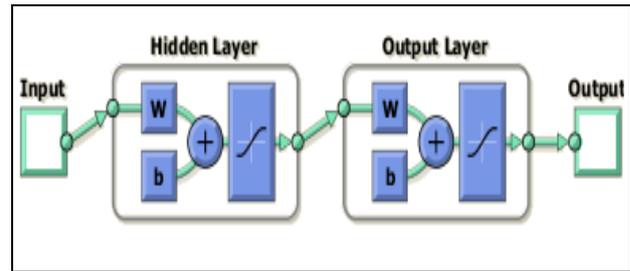
ANN structure is an interlinked assembly of individual processing elements called nodes. Each node receives inputs from neighbouring nodes, processes the information with selected transfer function and produces an output to be transmitted to the next node. The strength of connections between the two units is called weights. These nodes are arranged in the form of layers. The most common structure is a three-layered network which includes an input layer, a hidden or interactive layer and an output layer. See Figure 4.



**Fig. 4.** A Simple three layered ANN.

The architecture design of a neural network is depend on the application. Feed-forward ANNs allow signals to travel one way only from input to output as shown in Figure 4. Whilst feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. Both are extensively used in pattern recognition. However, the quality of results is dependent on the selection of a suitable transfer function in the hidden and output layers. The sigmoid transfer function commonly used when two case need to be classified. Therefore, the Log-sigmoid transfer function was used; from pattern

recognition tool box in MATLAB, to generate the network in the hidden and output layer. See Figure 5.

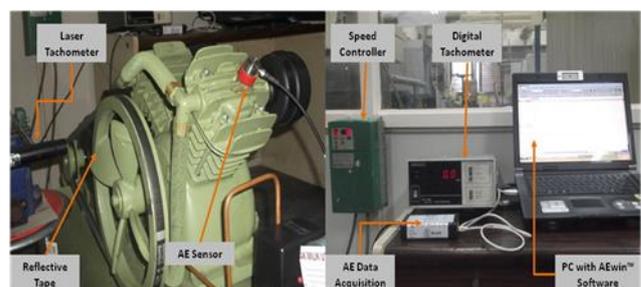


**Fig. 5.** Feed-Forward Back-Propagation as selected from MATLAB

### 3. Research Methodology

#### 3.1. Test Rig and Instrumentation

The test rig employed for this study consists of a single stage, 2 cylinders and air cooled industrial reciprocating air compressor (model: SWAN SVP-202) with 1.5kW/2hp motor that can provide maximum operational speed up to 820rpm. A digital laser tachometer is configured and fixed with the test rig to receive a pulse from a reflective tape attached to the flywheel in order to show the compressor cycle and to record the compressor speed. The transducer employed for AE data acquisition; a piezoelectric type AE sensor (Physical Acoustic Corporation type PKWDI) with an operating frequency range of 200 kHz - 850 kHz, were placed directly on the valve housing of the reciprocating compressor and held firmly to the surface by using super glue as a couplant. See Figure 6.



**Fig. 6.** Test rig and data acquisition setup.

A single channel AE data acquisition (DAQ) system (model: USB AE Node) with 18-bit resolution providing a full AE hit and time-based features was used for AE signal collection. AEwin™ software was used for recording AE hits and extracting AE parameters. The AE signals were acquired at a sampling rate of 500 kHz, for a total of 1024 data points per acquisition (data file). The signal was recognized perfectly at a threshold level of 55 dB. The AE signals were digitized and conditioned by the DAQ device before transmission to a computer for further analysis.

#### 3.2. Experimental Procedure

Before inducing the faults at reciprocating compressor discharge and suction valves, AE base line signal (free defect) was recorded. The experiment include for 39 operational conditions; thirteen speed ranging from (200 rpm) to (800 rpm) with incremental increasing by (50rpm) and three flow rate conditions ranging from (0%, 50% and 100%). Speeds were controlled by the speed controller while the flow rate was simulated by controlling the flow from compressor outlet valve.

Two types of faults; corrosion and clogged, were simulated at the discharge and suction valves separately and then induced to the reciprocating compressor individually. The simulation of both defects involved starting a sequence on a valve with simulating a small size defect and increasing the area of defect gradually to achieve the maximum size of the possible fault. The simulation of the corrosion defect involved making a hole with an oval shape; a similar way to the actual defect of the corrosion, using a drilling machine. Thus, five different size of corrosion were simulated. The clogged defect was conducted by sealing some of the valve outlet holes using welding to emulate the condition of valve clogged due to excessive dirt or from the excessive oil distribution which can make the reed to be stick then to be clogged. Thus, two different sizes of clogged were simulated on the valve. A total of sixteen conditions signal were recorded (8 valve conditions multiplied by 2 kind of valve: suction and discharge) with each of the 39 operational conditions to give a total of 624 tests that have been done. For accuracy reason, three sets of data have been acquired for each test then the average were calculated and taken as a final result. Table 2 illustrates the type of defects with their severities.

**Table 2.** Defects type and severities.

Valve State	Defect Type	Defect Severity	Defect Symbol	Defect Ratio (%)
Healthy State	No Defect	Normal Condition	ND	No Defect
Faulty State	Corrosion Defect	Very Small Corrosion	VSC	37.07 mm <sup>2</sup>
		Small Corrosion	SC	56.57 mm <sup>2</sup>
		Medium Corrosion	MC	79.63 mm <sup>2</sup>
		Large Corrosion	LC	106.27 mm <sup>2</sup>
		Very large Corrosion	VLC	136.48 mm <sup>2</sup>
	Clogged Defect	Moderate Clogged	MCL	40 %
		Intense Clogged	ICL	80 %

Experimental tests were performed by first making the defects in the appropriate size and geometrical shape at valves. The valves then were configured inside the reciprocating compressor. Thus, the test rig was operated at first speed and flow rate condition. The signal was recorded for 30 sec then the process was repeated for 3 times. Then the test rig was shutdown and the valves were replaced to provide another fault severity.

All experiments were conducted at laboratory temperature range between 25-30°C and standard atmospheric pressure. Thus, a total of 142035 data samples for AE signal statistical parameters were obtained from the experimental tests. According to hold and train method [29], the data were divided randomly into two groups: 85% as the training set, including 120823 data samples, and 15% as the validation set, including 21212 data samples. Training samples were used to develop the model, while the validation samples were held out and then applied to the developed model to evaluate the model performance.

### 3.3. The Concept of Training and Testing in ANN

Generally, training and testing are the most important computation that takes place in ANN method. When the training is complete, a relationship between input and output data can be established. Through training, the node weighting is keep adjusted till the value get close to the real value of all available inputs. Nevertheless, once an over fitting is identified the computational processing will stop. Over fitting takes place when the model is performing well during training; then it starts to decline when tested with hidden data. Figure 7 illustrate the schematic diagram of all steps involved in the modeling by ANN.

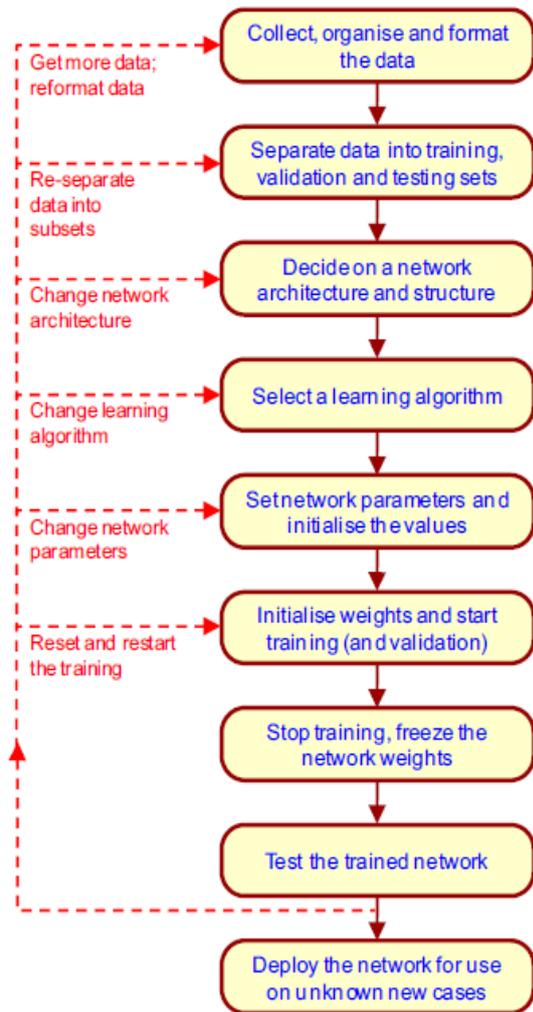


Fig. 7. Schematic representation of the steps involved in atypical ANN [30].

Cross-validation which estimates the performance of a predictive model can overcome over fitting. Training and validation require two different data sets. Two statistical error values in training and testing were used to check modeling process in this research which is the mean squared error (MSE) and the percent error (%E). Mean squared error is the average squared difference between outputs and targets the lower values are better (Zero means no error) whilst percent error indicates the fraction of samples which are misclassified (A value of 0 means no misclassifications and value of 100 indicates maximum misclassifications).

Thus, the mean squared error (MSE) of the validation data first decreases when over fitting takes place, reaches a minimum, and then increases. However, the training data MSE continues to decrease. It is assumed that when the validation data set MSE increases, the regression algorithm is over fitting the training data and training will be stopped [31]. In this study, the supervised training method was used to classify the compressor valve into healthy or faulty. Thus, the ANN developed with 11 neurons for input include AE hit duration, count, count to peak, amplitude, RMS, average signal level (ASL), signal strength, energy and absolute energy. Moreover,

two operational conditions added to the input which is speed and flow rate.

The number of neurons in the hidden layer is assumed to be the number of inputs multiplied by two, plus one (number of inputs  $\times 2 + 1$ ) [32]. Thus, 23 neurons have been used for the hidden layer and only 2 neurons for output layer which are healthy / faulty. During testing process, the real output is compared to the ANN output. At this point the connection weights are still not adjusted yet and the data are collected, converted, and a comparison is made. After training finish, the network is suitable for use when testing shows it is able to process the correct answers. Hold and train method have been used automatically by MATLAB to generate and validate the model at the same time, in other words, the software divided AE parameters data randomly into 70% of data for train and 15% for both test and validation process. Training samples were used to develop the model. Test samples are used to check the model during training and validation samples were hold-out then applied to the developed model to evaluate the model's performance.

#### 4. Results and Discussions

Neural network toolbox in MATLAB has many types of training algorithms and training functions. However, pattern recognition toolbox was used with feed forward back propagation (FFBP) networks to train the data and to develop the model in this study.

Table 3 illustrates the value of the statistical errors which have been done during the training, validation and testing stages for the developed network. The statistical errors have been used to assess the performance of the networks. The result indicates that the performance of networks in training is not so much different with the testing for the FFBP, whereas the value of the errors measurement in training is a little less than the testing. Which means the network is valid for classifying the valve condition.

Table 3. ANN mean squared error and percent error.

Samples Data	Samples Number	MSE	%E
Training	99425	2.00096e-2	2.31430e-2
Validation	21305	2.08152e-2	2.31870e-2
Testing	21305	2.07484e-2	2.32809e-2

##### 4.1. Neural Network Performance

The advantage of pattern recognition FFBP network is that it is easy to construct. During the development of the network, and after all the parameters (input layer,

hidden layer and output layer) are established, the weights and biases of the network are saved as one model. Therefore, the performance is evaluated by plotting the MSE error against the number of epochs of ANN training. Training MSE is always decreasing till get the smallest error. Figure 8 illustrates the ANN performance. The figure shows the mean square error dynamics for all your three datasets in logarithmic scale. It is clearly shows that the best validation performance is  $0.020815 \times 10^{-2}$ . The error decrease 91 iterations revealing no more significant change in error with a further increase in the number of epochs. There are also less testing and validation errors, as seen from close proximity of the curves between the train, test and validation data.

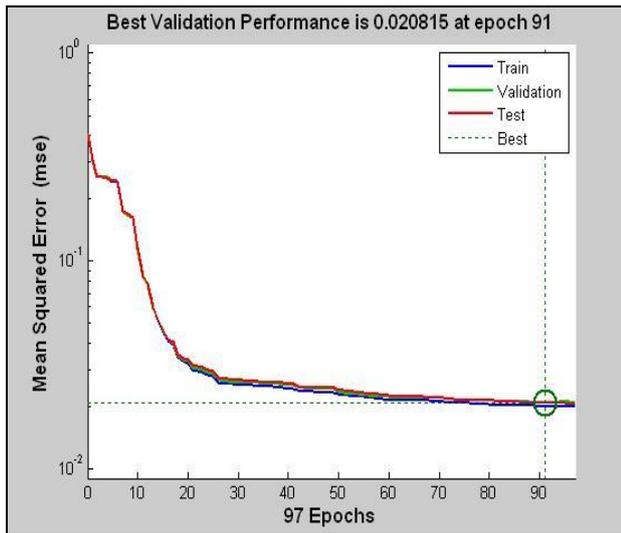


Fig. 8. The developed ANN performance graph.

#### 4.2. Ability of Classification and Error rate

After train the data and the model have been fit, it is important to know how much is the model accuracy. Therefore, the model classification ability is calculated on the probability scale. Thus, cutoff value of 0.5 is set and all predicted values above that cutoff value is predicting healthy and all below is predicted faulty. Figure 9 illustrates the model accuracy for the ANN. The figure shows the confusion matrices for training, testing, and validation, and the three type of data combined. The network outputs are very accurate, as shown by the high numbers of correct responses in the green squares and the low numbers of incorrect responses in the red squares. The lower right blue squares illustrate the overall accuracies. Thus, the model presents an overall accuracy of 97.7% with 2.3% error rate which is excellent for classify the valve condition.

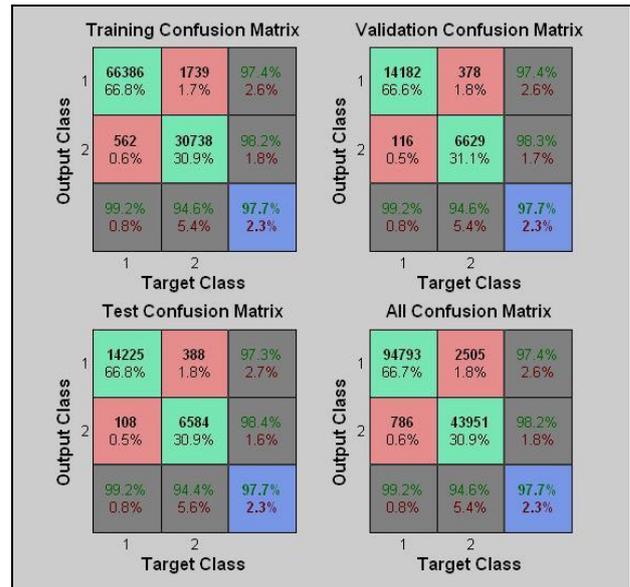
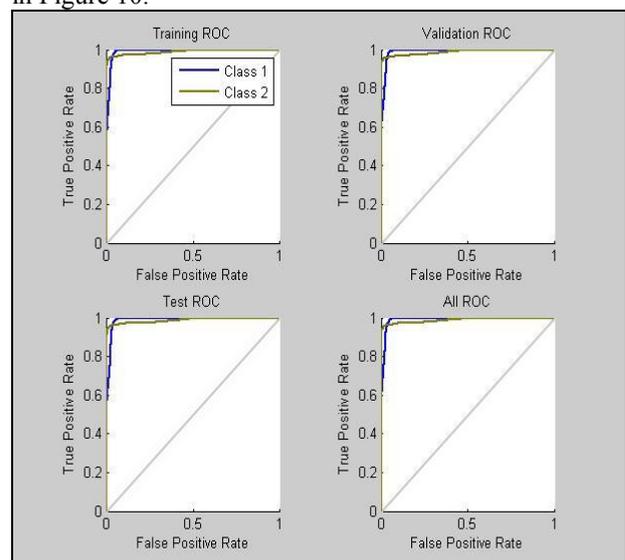


Fig. 9. ANN confusion matrix for training, testing, validation and the overall accuracy.

#### 4.3. Receiver Operating Characteristic (ROC) Curve

Another essential measure for the model discrimination accuracy is by plotting the receiver operating characteristic curve. ROC curve usually used to assess the fit of a pattern recognition model when the output is binary (0 or 1) or healthy / faulty. It is based on the simultaneous measure of specificity (or the negative) and sensitivity (True positive) for all probable cut-off points. First, the software calculate sensitivity and specificity pairs for each data set for training, testing and validation at each possible cut-off point and plot sensitivity on the y axis by (1-specificity) on the x axis. The area under the ROC curve ranges from 0.5 and 1.0 with larger values indicative of better discrimination. Therefore, the area with larger values always indicative of better fit. Thus, the ROC curve details for the diagnoses model illustrate in Figure 10.



**Fig. 10.** ROC curves.

The area under the curve is representing an excellent model fit with high discrimination accuracy. The accuracy of the test depends on how well the AE parameters discriminate the conditions being tested into those faulty and healthy conditions. Note that the point on the curve that is nearest to the upper left corner represent to the cut-off value that will maximize the specificity and sensitivity of the model discrimination.

## 5. Conclusion

The study proposed a fault detection technique based on AE parameters and ANN. The results showed that FFBP was effective and this suggested technique attained 100% success in prediction and classification at high speed during training. An experimental procedure was conducted on a single stage industrial reciprocating compressor and consisted of inducing two typical valve faults in the compressor with different severity. Data was tabulated according to the valve condition then ANN model was developed based on training samples of the AE signal parameters. The model was validated by using other validation samples never train the model. Based on predictive accuracy and the ROC curve, the results demonstrated that the SVM model could classify 97.7% of valve condition correctly. Moreover, ROC curves illustrating maximum sensitivity and specificity by the ANN model. It is concluded that the proposed ANN model can be used with utmost accuracy to diagnosis valve condition in a single stage reciprocating compressor. Eventually, the authors intend to do more efforts for programming this model in smart portable device which can be one of the innovative engineering technologies in the field of machinery condition monitoring in the near future.

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